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Understanding How Internet Addiction Influences Digital Distraction in Online Courses: Implications for Information Systems Education

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ABSTRACT

Internet addiction (IA) and digital distraction are pervasive technology use problems in both education and professional settings and are often studied as key topics in the domain of "dark side of technology" in IS research. Prior research has shown that higher IA levels lead to greater digital distraction but has lacked a theory-driven explanation for this relationship. This study investigates the impact of IA on digital distraction through the lens of cognitive dissonance. Using data collected from online students, we find that distraction intensity is partly regulated by post-behavior dissonance and that IA evokes cognitions that rationalize distraction, thereby reducing dissonance and amplifying distraction. These findings advance the theory and offer practical guidance for curbing digital distraction among students. Importantly, they underscore the educational relevance of IA and digital distraction and provide IS educators with insights into the psychological factors they can address to reduce off-task technology use in online and technology-enhanced classrooms.

Keywords: Digital distraction, Internet addiction, Cognitive dissonance, Technology-enhanced education

1. INTRODUCTION

In an increasingly digitalized world, information and communication technology (ICT) tools such as smartphones and laptops have become essential in everyday life (Chen et al., 2014; Wong et al., 2018). While they provide invaluable benefits, ICT devices also introduce the challenge of digital distraction, defined as the behavioral and attentional shift away from a primary task toward an unintended one (Chen et al., 2020; Flanigan et al., 2022). Unlike multitasking (e.g., listening to music while studying), digital distraction is a technology misuse and implies disengagement from the intended task. Examples of digital distraction include students browsing social media during lectures or employees checking personal emails during work meetings. Such distractions undermine learning outcomes, reduce productivity, and create challenges for both educators and organizations (Khansa et al., 2017; Wu et al., 2018).

Therefore, digital distraction has become a growing concern for educators in information systems (IS) and related fields as it undermines student engagement and learning outcomes in technology-enhanced classrooms and online courses. ICT tools are used pervasively in IS courses, and that makes the management of students' attention a pedagogical challenge. Instructors and academic institutions need to understand the root causes of the problem and seek evidence-based strategies to mitigate digital distraction to maintain effective learning environments. This study aims to address this issue in IS education and

explore the issue of how to harness technology for learning while minimizing its potential to create distraction.

A key factor associated with digital distraction is Internet addiction (IA), defined as an excessive and uncontrolled need to use the Internet that negatively affects effectiveness, health, and relationships (Chen et al., 2014). IA, often referred to as problematic or compulsive Internet use, has been linked to reduced productivity, procrastination, and heightened distraction (Nath et al., 2015; Widyanto et al., 2011). Although prior studies have established the association between IA and digital distraction (Chen et al., 2014; Chen et al., 2020), they have not explained why this relationship exists.

A major contribution of this paper is its being the first empirical investigation of the impact of IA on digital distraction through the lens of cognitive dissonance. This perspective advances theoretical development in the area and provides actionable insights for reducing the intensity of digital distraction. Cognitive dissonance refers to the psychological discomfort individuals experience when their behaviors conflict with their beliefs or values (Festinger, 1957). Our study posits that, like other problematic behaviors (e.g., smoking, gambling), the intensity of digital distraction is partially regulated by cognitive dissonance. Individuals who experience post-distraction dissonance may attempt to reduce future distractions, whereas others may rationalize their behavior and continue. We propose that IA and its underlying constructs may propel the development of cognitions that are consonant with or rationalize digital distraction behaviors to reduce the individual's cognitive dissonance leading to higher digital distraction intensity.

The remainder of the paper is structured as follows. The next section provides a comprehensive literature review of the key constructs and theoretical background relevant to the study. Afterward, we present the research model of this study and the rationale behind the proposed hypotheses. This is followed by a discussion of research methodology, including data collection and measurement development. Then, we present the data analysis results and discuss the key findings. Finally, we conclude with theoretical and practical implications, as well as limitations and future research directions.

2. LITERATURE REVIEW

While ICT tools provide significant benefits in education and work, not all technology use serves its intended purpose. For example, digital distraction is a prevalent form of technology misuse, poses harmful consequences, and has become a critical issue. IS research on this topic remains limited and tends to focus on three major streams: prevalence and negative effects, determinants, and mitigation strategies. The first stream highlights the widespread nature and negative outcomes of digital distraction. High mobile device ownership and ubiquitous Internet access have fueled its rise. Studies show college students use mobile phones for off-task purposes 25-30% of class time, and laptops are used for off-task activities during 63% of lecture time (Kim et al., 2016; Ragan et al., 2014). At work, employees spend from 3 hours weekly to 5-6 hours daily on non-work activities (Kim et al., 2016). Distractions range from texting and browsing to more extreme behaviors like gambling or visiting adult sites (Blanchard & Henle, 2008). These behaviors cause cognitive overload, reduce focus, inhibit deeper learning, degrade academic performance, and are contagious in classrooms (Aaron & Lipton, 2018; Flanigan et al., 2022; Wu et al., 2018). In workplaces, cyberloafing costs companies billions annually in lost productivity (Rosen & Samuel, 2015) while also increasing stress, disrupting sleep, and causing injury in industries such as manufacturing (Archer, 2014; Phelan, 2021). Collectively, these findings reveal the growing severity of digital distraction for both learning and productivity.

The second stream examines the determinants of digital distraction. Demographics such as age, gender, and high Internet use correlate with distraction (Baturay & Toker, 2015; Chen et al., 2014; Chen et al., 2020). Psychological traits are equally influential. Guided by the theory of reasoned action, Taneja et al. (2015) identify escapism, apathy, attitudes, and norms as predictors. Other studies highlight the brain's impulsive, automatic, and reflexive mechanisms as a reason for distraction (Turel & Qahri-Saremi, 2016). Supporting this assertion, empirical findings show attention impulsiveness, IA, and habitual use drive distraction (Chen et al., 2020), and online vigilance and FOMO (fear of missing out) exacerbate this behavior (Schneider & Hitzfeld, 2021).

The third stream of research explores intervention strategies, particularly in IS education. Proposed strategies include raising awareness, enforcing policies, active learning, and integrating technology as a learning tool (Flanigan & Kiewra, 2018; Kuznekoff, 2022; Perez-Juarez et al., 2022). However, critics of these strategies argue that such approaches burden instructors without addressing the root causes (Luo & Kiewra, 2022). Effectiveness may depend on intentionality: for example, self-regulation strategies work for deliberate distraction (Brady et al., 2021; Inzlicht et al., 2021; le Roux & Parry, 2022), but they are less effective when behaviors are automatic and impulsive (Chen et al., 2020).

IA contributes to reduced productivity, procrastination, digital distraction, and psychological disorders such as diminished impulse control, loneliness, depression, and dependence on the Internet for social comfort (Chen et al., 2020; Davis et al., 2002; Widyanto et al., 2011). Among college students, IA is linked to mood changes, withdrawal symptoms, social decline, reduced academic performance, and suicidal ideation (Kumar & Mondal, 2018). Its symptoms resemble substance addiction, including preoccupation, restlessness, mood swings, failed attempts to cut back, and denial, and these are often accompanied by physical issues like sleep disturbances and headaches (Griffith, 2012; Kumar & Mondal, 2018; Rosen & Samuel, 2015).

Individuals with prior addictive or psychiatric histories, such as anxiety or depression, are at higher risk of developing IA (Gao et al., 2021; Ko et al., 2009). In addition, those with interpersonal difficulties, such as introversion or low social skills, often turn to online relationships to mitigate loneliness (Ebeling-Witte et al., 2007; Young, 2017). Other predictors of IA include family dynamics, substance use, heavy social media/gaming use, hours online, gender, and Internet access mode (Kapus et al., 2021; Kumar & Mondal, 2018; Weinstein & Lejoyeux, 2010). Although the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) recognized Internet gaming disorder (IGD) in 2013, IA often remains undiagnosed. Young's (1998) Internet Addiction Test (IAT) remains a widely used diagnostic tool. Widyanto et al. (2011) validated the IAT and identified three underlying constructs that define IA collectively: psychological/emotional conflict, time management issues, and mood modification. These dimensions explain IA's escapist tendencies, avoidance of responsibilities, and reliance on the Internet for emotional relief. The instrument has since been used extensively in IA research (e.g., Chen et al., 2014; Chen et al., 2020; Nath et al., 2015).

Since the beginning of the COVID-19 pandemic in early 2020, the Internet has become an extremely important medium for people to learn, work, communicate, entertain, and maintain personal relationships. As a result, the prevalence of Internet use and Internet-based addiction has increased among all age groups, compounded by heightened levels of stress, anxiety, and depression caused by the pandemic (Petrović et al., 2022). For example, a study in Japan reports that IA among adults increased by 3.2-3.7% compared to before the pandemic (Oka et al., 2021). Similarly, an online survey of over 20,000 participants in China finds that IA reached a prevalence of 36.7% in the general population during the pandemic (Li et al., 2021). The study also attributes increased recreational Internet use to low income, lack of social support, and experiences of negative life events, suggesting that IA is especially pervasive among the most vulnerable groups of the population.

Despite advances, IA research still lacks theoretical depth. While associations with deviant technology use such as digital distraction are well documented (Chen et al., 2008; Chen et al., 2020; Nath et al., 2015), explanations remain underdeveloped. Brand et al. (2014) suggest that the brains of Internet addicts react like those of substance abusers, while Turel et al. (2011) suggest that IA augments individuals' intrinsic (e.g., sense of accomplishment, joy, and purpose) and extrinsic (e.g., financial gains, recognition from others, and promotions) gain perceptions about the Internet. However, both stop short of explaining how IA causes misguided perception that would lead to technology misuse, overuse, and abuse. That is the aim of this study.

This study uses cognitive dissonance theory to examine the relationship between IA and digital distraction. Festinger's (1957) cognitive dissonance theory explains the mental stress and discomfort individuals experience when they hold two conflicting cognitions or engage in behaviors that do not align with their existing cognition. Dissonance generates negative emotions such as stress or guilt (Festinger, 1962), with its magnitude depending on the ratio of dissonant to consonant cognitions and the importance

of conflicting cognitions (Harmon-Jones & Mills, 2019). For example, individuals who are aware of smoking's harms yet continue the behavior would experience dissonance, while rationalization (e.g., "It's only harmful if I smoke daily") reduces discomfort (Vaghefi & Qahri-Saremi, 2017). Strategies to reduce dissonance include changing the behavior, rationalizing, adding new cognitions, or minimizing the importance of the conflicting cognitions (Cummings & Venkatesan, 1976; Eiser et al., 1978; Festinger, 1957). Because humans seek internal psychological consistency, cognitive dissonance drives people to engage in behaviors to reduce their dissonance (Cooper, 2007). While these coping mechanisms restore consistency, rationalization and denial often perpetuate problematic behaviors such as smoking or gambling (Rose, 2015).

The theory has been applied across education, psychotherapy, consumer behavior, politics, and communication. Post-purchase dissonance, for example, is managed by rationalizing or returning the product (Powers & Jack, 2013). The theory is especially useful for studying problematic behaviors, as individuals justify actions despite knowing their harms (Festinger, 1957). When applied to digital distraction, cognitive dissonance may prompt individuals to reduce off-task behaviors if guilt dominates (Baumeister et al., 1994). However, rationalization can perpetuate and intensify distraction. Addicts often engage in delusional reasoning to protect self-image (Evans, 1998; Heshmat, 2016) and reinforcing harmful behaviors (Vaghefi & Qahri-Saremi, 2017). These insights suggest cognitive dissonance provides a valuable lens for understanding how IA influences digital distraction.

3. RESEARCH MODEL AND RELATED HYPOTHESES

Figure 1 displays the research model for this study. This research model examines how IA influences Digital Distraction through Cognitive Dissonance. IA's components, psychological/emotional conflict, time management issues, and mood modification, positively drive consonant or rationalizing cognitions, which in turn reduce emotional and behavioral dissonance. Lower dissonance eventually increases digital distraction. The associated hypotheses and the rationales behind them are discussed in this section.

In online education, cognitive dissonance arises when students compare their digital distraction behavior with their perception of its rightness. When behavior and perception conflict, dissonance occurs to produce a negative state that motivates strategies to reduce discomfort (Elliot & Devine, 1994; Festinger, 1957; Sweeney et al., 2000). Such dissonance is highly likely as most instructors of online courses stress the importance of not using technologies for purposes unrelated to the course work during the class, and in some cases, specify consequences or penalties for such actions (Flanigan et al., 2022). Students experiencing strong post-distraction dissonance may refrain from future distraction, while those with low dissonance may persist. In other words, higher levels of cognitive dissonance in individuals would lead to lower digital distraction intensity, and vice versa.

Cognitive dissonance has been linked to anxiety and remorse (e.g., Insko & Schopler, 1972; Menasco & Hawkins, 1978). Sweeney et al. (2000) argue that dissonance has both cognitive and emotional components and should be measured as such. Using post-purchase dissonance experienced by consumers, Sweeney et al. (2000) propose a three-dimensional instrument that includes the emotional, wisdom of purchase, and concern over deal constructs. In the context of digital distraction, this study focuses on the first two constructs of dissonance specified by Sweeney et al. (2000), as the decision to engage in digital distraction behaviors is assumed to be made individually, without external intervention during online classes. Therefore, in this study, the emotional construct is adapted to measure the psychological discomfort the individual experiences after performing digital distraction behaviors, and the construct is named "emotional dissonance" (ED). The wisdom of purchase construct is adapted to measure the individual's doubts about the rightness and/or necessity of performing digital distraction behaviors during an online class; therefore, the construct is named "Behavioral Dissonance" (BD) to emphasize its association with the specific behavior under study. Collectively, ED and BD are designed to represent and measure the level of cognitive dissonance the individual experiences. Based on this rationale, we propose the following hypotheses:

H1: An individual's emotional dissonance (ED) negatively influences their level of digital distraction intensity.
H2: An individual's behavioral dissonance (BD) negatively influences their level of digital distraction intensity.

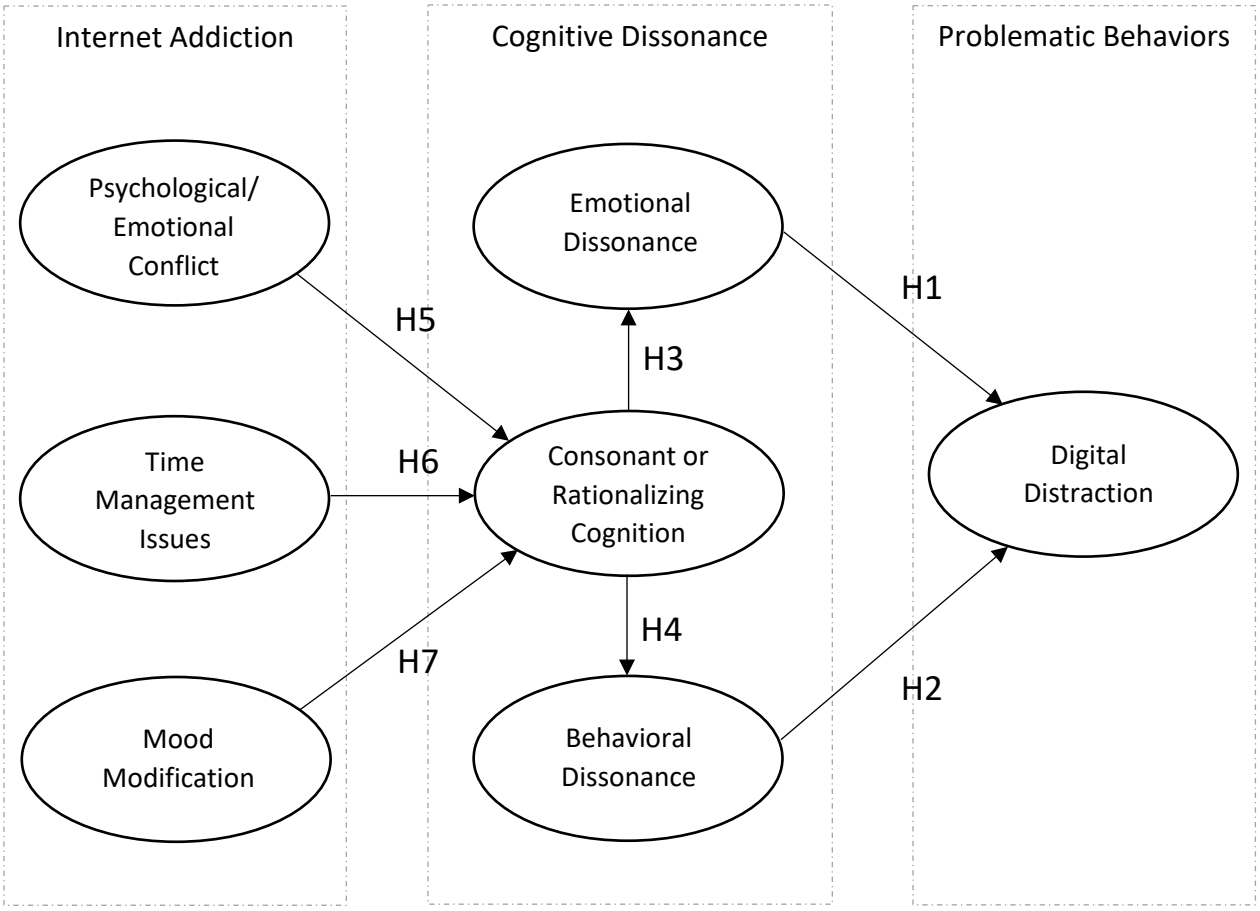


Figure 1. Research Model

A person is in a dissonant state when two cognitive elements are inconsistent. In online education, class policies and the social stigma surrounding digital distraction likely arouse dissonance after students engage in off-task behaviors, especially when instructors repeatedly warn against them. According to dissonance theory, individuals reduce this discomfort by rationalizing, in other words, downplaying negatives or adding positives to make the action seem more acceptable (Harmon-Jones & Mills, 2019). As Festinger (1957) argued, people often resolve dissonance by convincing themselves of what they want to believe.

The magnitude of post-behavior dissonance depends on the *dissonance ratio*, defined as the number of dissonant cognitions relative to consonant ones (Festinger, 1957; Harmon-Jones & Mills, 2019). Holding dissonant cognitions constant, the ratio rises when consonant cognitions decrease and falls when they increase. Thus, rationalization serves as a strategy to lessen discomfort by boosting consonant cognitions in favor of digital distraction. Rationalization provides psychological consistency between actions and beliefs. For instance, smokers with no intention to quit rationalize their behavior by endorsing positive beliefs such as "smoking calms me down" and minimizing risks with statements like "the link between smoking and lung cancer is exaggerated" (Fotuhi et al., 2013). Similarly, dissonant individuals often exhibit confirmation bias – accepting only information that supports their behavior while disregarding

disconfirming evidence (Tavris & Aronson, 2007). Applied to digital distraction, students may rely on consonant or rationalizing cognitions to justify their off-task behaviors and reduce dissonance. Therefore, we propose the following hypotheses:

H3: An individual's consonant/rationalizing cognitions for digital distraction negatively influences their emotional dissonance.
H4: An individual's consonant/rationalizing cognitions for digital distraction negatively influences their behavioral dissonance.

Individuals with strong beliefs or tendencies often cling to their attitudes despite well-reasoned disconfirming information (Aronson et al., 2019). For example, smokers in Cohen and Kassarjian's (1965) study doubted reports linking smoking to cancer, and similar cognitive distortions have been observed elsewhere (Gilovich et al., 1995; Losciuto & Perloff, 1967). According to self-affirmation theory, people defend self-defining opinions to protect a positive self-image and reject disconfirming evidence when it feels self-threatening (Cohen et al., 2000). When the self-image is threatened, individuals rationalize regrettable decisions to restore a sense of competence or morality (Aronson et al., 2019). Therefore, students labeled as "disruptive" or employees branded "lazy" for digital distraction may rationalize their behavior to mitigate stigma.

IA exacerbates this defense mechanism in two ways. First, IA is marked by dependence on technology, weak self-control, and negative consequences such as reduced productivity, procrastination, diminished impulse control, loneliness, and depression, all of which harm self-image and self-worth (Chen et al., 2014; Chen et al., 2020; Widyanto et al., 2011). Second, cognitive dissonance theory posits that the more personally valuable the inconsistent beliefs or behaviors, the greater the dissonance (Festinger, 1962). Therefore, it is reasonable to assert that an elevated level of IA would lead to a stronger motivation to rationalize digital distraction behaviors. To assess IA, Widyanto (2011) recommends evaluating three underlying constructs of the Internet Addiction Test (IAT): emotional/psychological conflict, time management issues, and mood modification. Although all these dimensions capture IA's adverse effects, each may influence rationalization differently. Therefore, we examine their separate impacts on consonant or rationalizing cognitions as hypothesized below:

H5: An individual's psychological/emotional conflict positively influences their consonant/rationalizing cognitions for digital distraction.
H6: An individual's time management issues positively influence their consonant/rationalizing cognitions for digital distraction.
H7: An individual's mood modification positively influences their consonant/rationalizing cognitions for digital distraction.

4. RESEARCH METHODOLOGY

4.1 Measurement Development

To validate the research model and hypotheses, this study uses a digital distraction scenario in which students in synchronous online courses use devices (e.g., computers, smartphones) for non-course-related activities. This scenario also reflects remote work settings with limited supervision, allowing broader generalization of findings. Table 1 presents the constructs and measurement items.

Internet addiction was measured using Widyanto et al.'s (2011) adaptation of IAT, which captures three factors: Emotional/Psychological Conflict, Time Management Issues, and Mood Modification. Emotional and Behavioral Dissonance scales were adapted from Sweeney et al. (2000) and Powers and Jack (2013) for the context of digital distraction. All constructs were measured with multi-item, five-point Likert scales (1 = strongly disagree, 5 = strongly agree). Digital distraction intensity was assessed using items from Chen et al. (2020), which measured how frequently participants engaged in non-class-related device use on a five-point scale (1 = never, 5 = very frequently).

Psychological/Emotional Conflicts	
PC1	Do you prefer the excitement of the Internet to intimacy with your friends or family?
PC2	Do others in your life complain to you about the amount of time you spend online?
PC3	Does your job/school performance or productivity suffer because of the Internet?
PC4	Do you become defensive or secretive when anyone asks you what you do online?
PC5	Do you block disturbing thoughts about your life with soothing thoughts of the Internet?
PC6	Do you find yourself anticipating when you will go online again?
PC7	Do you try to cut down the amount of time you spend online and fail?
PC8	Do you try to hide how long you've been online?
PC9	Do you choose to spend more time online over going out with others?
Time Management Issues	
TM1	Do you find that you stay online longer than you intended?
TM2	Do you neglect household chores to spend more time online?
TM3	Does your work suffer (e.g., postponing things, not meeting deadlines, etc.) because of the amount of time you spend online?
TM4	Do you check your e-mail before something else that you need to do?
TM5	Do you find yourself saying "Just a few more minutes" when online?
Mood Modification	
MM1	Do you form new relationships with fellow online users?
MM2	Do you fear that life without the Internet would be boring, empty, and joyless?
MM3	Do you snap, yell, or act annoyed if someone bothers you while you are online?
MM4	Do you lose sleep due to late-night log-ins?
MM5	Do you feel preoccupied with the Internet when off-line, or fantasize about being online?
MM6	Do you feel depressed, moody, or nervous when you are off-line, which goes away once
Consonant/Rationalizing Cognitions	
CR1	I am allowed to use the computer/mobile phone for activities not related to the class during the online class to relax every once in a while.
CR2	I should be allowed to use the computer/mobile phone for activities not related to the class during the online class if I do not find the lecture interesting or useful.
CR3	I will make up what I missed while using the computer/mobile phone for activities not related to the class during the online class by studying more later.
CR4	Using the computer/mobile phone for activities not related to the class during the online class is not causing anyone any harm.
Emotional Dissonance	
ED1	After I have used the computer/mobile phone for activities not related to the class during the online class, I felt uneasy.
ED2	After I have used the computer/mobile phone for activities not related to the class during the online class, I felt I let myself down.
ED3	After I have used the computer/mobile phone for activities not related to the class during the online class, I felt depressed.
ED4	After I have used the computer/mobile phone for activities not related to the class during the online class, I felt hollow.
ED5	After I have used the computer/mobile phone for activities not related to the class during the online class, I felt emotionally distressed.
Behavioral Dissonance	

BD1	I wonder if I really needed to use the computer/mobile phone for activities not related to the class during the online class after I have done so.
BD2	I wonder if I should have refrained myself from using the computer/mobile phone for activities not related to the class during the online class after I have done so.
BD3	I wonder if I have made the right choice to use the computer/mobile phone for activities not related to the class during the online class after I have done so.
BD4	I wonder if I have done the right thing by using the computer/mobile phone for activities not related to the class during the online class after I have done so.
Digital Distraction	
DD1	How often did you surf the Web for content that was NOT relevant to the class during the online classes in the last 6 months?
DD2	How often did you play computer/mobile phone games during the online classes in the last 6 months?
DD3	How often did you check social network sites (e.g. Facebook, Twitter, etc.) during the online classes in the last 6 months?
DD4	How often did you check and/or write emails during the online classes in the last 6 months?
DD5	How often did you read and /or send text or social media messages during the online classes in the last 6 months?
DD6	How often did you use the computer/mobile device for any activities that were NOT relevant to the class during the online class in the last 6 months?

Table 1. Constructs, Definitions, and Measurement Items

To assess consonant/rationalizing cognitions, the authors conducted interviews with thirty students who admitted engaging in digital distraction during online classes. Each student was asked to justify why using digital devices for off-task activities (e.g., browsing, social media, gaming, shopping) was acceptable. The interview scripts were analyzed to extract the consonant/rationalizing cognitions. The top four cognitions were: (1) distraction provides relaxation, (2) it is justified if the lecture is boring or unhelpful, (3) lost learning can be recovered later, and (4) it causes no harm to others. These widely endorsed beliefs demonstrate strong content validity as they normalize or minimize the negative effects of distraction. As a result, they were adopted as measures of the Consonant/Rationalizing Cognitions construct in this study. The process of instrument development is consistent with the recommendations from MacKenzie et al. (2011).

4.2 Data Collection

Students enrolled in eight sections of the same online course over two terms at a major public university were recruited to participate in this study. Because the course is a required course for all students, the sample includes students from a wide range of academic and socio-economic backgrounds. In addition to including statements in the course syllabi prohibiting digital distraction behaviors during online class meetings, the instructors repeatedly reminded the students throughout the term not to perform off-task technology use in class. At the end of the term, students were asked to complete an anonymous questionnaire consisting of the measurement items discussed previously and questions about general demographic information. They were instructed to reflect in their responses on their cognition and in-class behaviors related to the online class they were attending at the time. Table 2 displays the profiles of the respondents. Because the course is designed for second-term sophomores and first-term juniors, the great majority of the respondents are between the ages of 20 and 22 and are second- or third-year college students. There are slightly more male respondents than female respondents, and the Internet usage pattern of the respondents follows a normal distribution.

Characteristic	Items	Count	Percent
Gender	Male	215	57.33%
	Female	160	42.67%
Age	<20	114	30.40%
	20-22	251	66.93%
	23-25	8	2.13%
	26-30	2	0.53%
Year in school	1th year	32	8.53%
	2th year	132	35.20%
	3th year	128	34.13%
	4th year	83	22.13%
Daily online time	< 30 minutes	8	2.13%
	30 minutes to 1 hour	51	13.60%
	1-2 hours	102	27.20%
	2-4 hours	148	39.47%
	>4 hours	66	17.60%

Table 2. Sample Profiles

We evaluate the non-response bias by comparing the characteristics of the early respondents and those of the late respondents. Following the recommendation of Cheung et al. (2013) and Jin et al. (2017), we compare the first 50 responses with the last 50 responses. Our results show no statistically significant difference between the early and late respondents in terms of their demographics or responses to the survey items. Therefore, we conclude that there is no concern regarding the non-response error in this study.

5. DATA ANALYSIS

This study employs Partial Least Squares (PLS) path analysis as the primary research methodology. PLS is well suited for exploratory research where the theoretical knowledge is not fully developed as in the case of the impact of IA on digital distraction (Chin, 2010). In this study, we use the widely accepted two-step approach for data analysis.

5.1 Measurement Model

Discriminant validity of the measurement model is assessed by comparing the square root of the average variance extracted (AVE) with the correlations between the constructs (Fornell & Larcker, 1981). Table 3 shows that all the square root of AVEs are lower than the correlations between construct pairs, suggesting that each construct is more strongly associated with its own measurement items than with other constructs; therefore, the results suggest that a sufficient level of discriminant validity exists in the data. In addition, the factor loadings and cross-loadings displayed in Table 4 indicate that the items' loadings on the constructs they are designed to measure are higher than cross-loadings. This offers further evidence that the items are more strongly related to the constructs they are designed to measure than to other constructs used in this study (Chin, 1998). These results confirm the presence of discriminant validity of the measurement model.

In addition to the discriminant validity, convergence validity is also assessed by reviewing the range of the loadings (Table 4) for each construct as suggested by Chin (2010). The ranges are all relatively narrow. For example, in the construct Psychological/Emotional Conflict, which is the construct with the greatest number of items, the loadings range from 0.607 to 0.826. For constructs with smaller numbers of items, the loading ranges are even narrower. Narrow ranges of loadings indicate greater confidence that the items agree strongly in their representation of the constructs they are designed to measure; therefore, we conclude that the measurement model demonstrates sufficient convergence validity.

	PC	TM	MM	CR	ED	BD	DD
Psychological/Emotional Conflict (PC)	**0.790**						
Time Management Issues ™	0.588	**0.767**					
Mood Modification (MM)	0.630	0.541	**0.789**				
Consonant/Rationalizing Cognitions (CR)	0.284	0.318	0.283	**0.831**			
Emotional Dissonance (ED)	-0.146	-0.052	-0.101	-0.342	**0.812**		
Behavioral Dissonance (BD)	-0.215	-0.120	-0.170	-0.289	0.360	**0.711**	
Digital Distraction (DD)	0.189	0.243	0.221	0.268	-0.289	-0.314	**0.758**

Table 3. Correlations Between Constructs

	PC	TM	MM	CR	ED	BD	DD
PC1	**0.826**	0.241	0.34	0.180	-0.136	-0.277	0.364
PC2	**0.793**	0.217	0.316	0.206	-0.142	-0.138	0.136
PC3	**0.607**	0.460	0.369	0.155	-0.170	-0.242	0.241
PC4	**0.727**	0.186	0.345	0.123	-0.214	0.059	0.404
PC5	**0.715**	0.300	0.414	0.191	-0.174	-0.116	0.230
PC6	**0.692**	0.385	0.461	0.255	-0.135	-0.149	0.118
PC7	**0.705**	0.568	0.401	0.115	-0.058	-0.155	0.207
PC8	**0.777**	0.328	0.358	0.149	-0.256	-0.207	0.219
PC9	**0.696**	0.319	0.404	0.212	-0.123	-0.162	0.034
TM1	0.451	**0.793**	0.384	0.306	0.225	-0.145	0.298
TM2	0.393	**0.688**	0.409	0.162	-0.116	-0.230	0.179
TM3	0.467	**0.857**	0.45	0.136	-0.215	-0.235	0.386
TM4	0.174	**0.784**	0.159	0.156	0.106	-0.001	0.204
TM5	0.527	**0.819**	0.485	0.269	-0.256	-0.182	0.182
MM1	0.350	0.276	**0.768**	0.086	-0.143	0.073	0.416
MM2	0.431	0.285	**0.751**	0.253	-0.129	-0.158	0.199
MM3	0.444	0.311	**0.761**	0.128	-0.262	-0.119	0.512
MM4	0.445	0.515	**0.741**	0.256	-0.219	-0.214	0.206
MM5	0.547	0.453	**0.690**	0.126	-0.092	-0.173	0.140
MM6	0.412	0.203	**0.832**	-0.006	-0.128	-0.148	0.262
CR1	0.190	0.266	0.223	**0.827**	-0.214	-0.164	0.286
CR2	0.188	0.265	0.238	**0.860**	-0.184	-0.106	0.312
CR3	0.130	0.233	0.204	**0.771**	-0.112	-0.143	0.305
CR4	0.228	0.289	0.271	**0.860**	-0.215	-0.150	0.320
ED1	0.001	0.043	-0.004	0.081	**0.750**	0.240	-0.204
ED2	-0.055	-0.015	-0.085	-0.214	**0.745**	0.042	-0.108
ED3	-0.107	-0.038	-0.098	-0.179	**0.693**	0.279	-0.173
ED4	-0.135	-0.083	-0.121	-0.109	**0.876**	0.322	-0.277
ED5	-0.113	-0.012	-0.036	-0.219	**0.827**	0.462	-0.379
BD1	0.001	-0.147	-0.138	-0.267	0.211	**0.734**	-0.200
BD2	-0.169	-0.152	-0.176	-0.107	0.181	**0.729**	-0.191
BD3	-0.188	-0.192	-0.180	-0.186	0.184	**0.811**	-0.304
BD4	-0.139	-0.120	-0.160	0.083	0.271	**0.841**	-0.155
DD1	0.198	0.226	0.209	0.308	-0.176	-0.287	**0.814**
DD2	0.082	0.152	0.168	0.114	-0.159	-0.243	**0.770**
DD3	0.227	0.248	0.252	0.321	-0.145	-0.209	**0.815**
DD4	0.125	0.134	0.077	0.274	-0.035	-0.136	**0.651**

DD5	0.077	0.143	0.134	0.315	-0.154	-0.229	**0.790**
DD6	0.141	0.182	0.124	0.344	-0.134	-0.263	**0.863**

Table 4. Loadings and Cross-Loadings

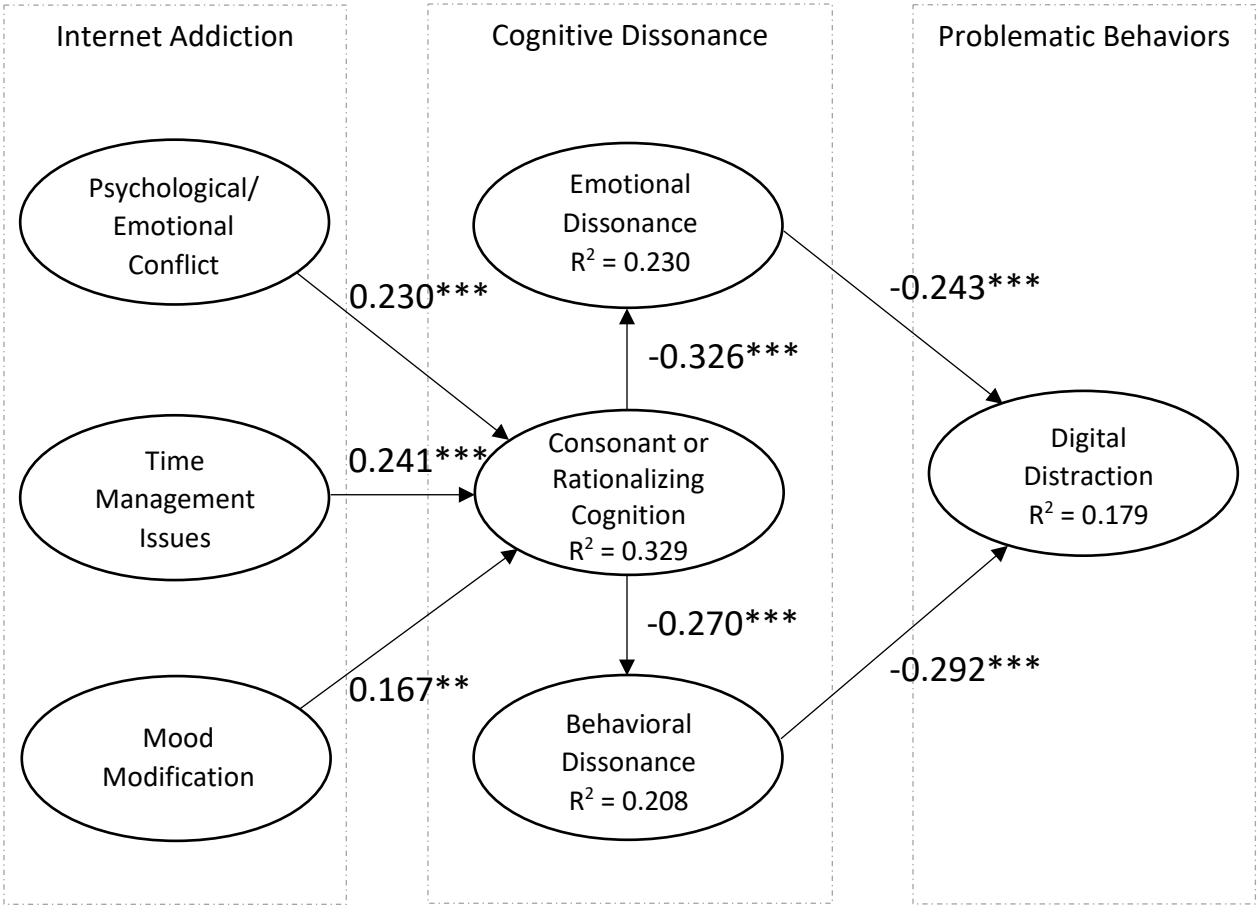
The Cronbach's Alpha, Composite Reliability (CR), and AVE (see Table 5) are used to evaluate the reliability of the measurement model. All Cronbach's Alpha and CR values are over the recommended threshold of 0.7, and all AVE values are above the recommended threshold of 0.5 (Fornell & Larcker, 1981; Hulland, 1999). Therefore, the results suggest that the measurement model of this study has both high reliability and validity.

	Cronbach's Alpha	CR	AVE
Psychological/Emotional Conflict	0.759	0.807	0.624
Time Management Issues	0.736	0.822	0.588
Mood Modification	0.765	0.810	0.622
Consonant/Rationalizing Cognitions	0.850	0.899	0.690
Emotional Dissonance	0.776	0.800	0.659
Behavioral Dissonance	0.877	0.930	0.505
Digital Distraction	0.848	0.888	0.574

Table 5. Cronbach's Alpha, Composite Reliability, and Average Variance Extracted

5.2 Structural Model

The second step in data analysis involves evaluating the validity of the structural paths in the proposed research model. A bootstrapping procedure (1,000 random samples of the 375 cases with substitutions) was employed to evaluate the significance of the path coefficients. Figure 2 displays a schematic representation of the resulting model with the estimated path coefficients. The results show that the components of IA, namely, Psychological/Emotional Conflict ($b = 0.230$, $p < 0.001$), Time Management Issues ($b = 0.241$, $p < 0.001$), and Mood Modification ($b = 0.167$, $p < 0.01$) all positively affect Consonant/Rationalizing Cognitions and collectively account for 32.9% of the variance in Consonant/Rationalizing Cognitions. Consonant/Rationalizing Cognitions influences both Emotional Dissonance ($b = -0.326$, $p < 0.001$) and Behavioral Dissonance ($b = -0.270$, $p < 0.001$) negatively. The effect accounts for 23% and 20.8% of the variance in Emotional Dissonance and Behavioral Dissonance, respectively. As expected, Emotional Dissonance ($b = -0.243$, $p < 0.001$) and Behavioral Dissonance ($b = -0.292$, $p < 0.001$) affect Digital Distraction intensity negatively and account for 17.9% of the variance in Digital Distraction. All the structural paths are statistically significant at the 0.01 level or better; therefore, all the proposed hypotheses are supported (see Table 6). Overall, the research model is found to be both theoretically meaningful and statistically well-fitting.



Note: * p < 0.05, ** p < 0.01, *** p < 0.001

Figure 2. PLS Analysis of the Research Model

Hypothesis	Hypothesized Relationship	Estimates (t-value)	Results
H1	Emotional Dissonance → Digital Distraction (-)	-0.243 (3.670)	Supported ***
H2	Behavioral Dissonance → Digital Distraction (-)	-0.292 (6.157)	Supported ***
H3	Consonant/Rationalizing Cognitions → Emotional Dissonance (-)	-0.326 (7.247)	Supported ***
H4	Consonant/Rationalizing Cognitions → Behavioral Dissonance (-)	-0.270 (4.374)	Supported ***
H5	Psychological/Emotional Conflict → Consonant/Rationalizing Cognitions (+)	0.230 (3.217)	Supported ***
H6	Time Management Issues → Consonant/Rationalizing Cognitions (+)	0.241 (3.505)	Supported ***
H7	Mood Modification → Consonant/Rationalizing Cognitions (+)	0.167 (2.716)	Supported **

Note: * p < 0.05, ** p < 0.01, ***p < 0.001

Table 6. Results of Hypothesis Tests

6. DISCUSSION

While IA has been found repeatedly to influence digital distraction intensity in prior studies, little is understood about why and how they are related. Through the lens of cognitive dissonance, this study is designed to understand the impact of IA on the level of intensity of digital distraction in an online education context. Specifically, this research proposes and validates a model that examines how the constructs of IA influence an individual's level of digital distraction intensity through the regulation of post-behavior dissonance. The results suggest that the research model and its associated hypotheses are supported by the data collected from 375 students enrolled in online courses.

This study yields three important findings. First, the research suggests that the theory of cognitive dissonance helps explain why individuals have different levels of digital distraction intensity, which is a form of problematic behavior in the online education and remote work environments. This research finds that individuals with lower cognitive dissonance, measured through emotional and behavioral dissonance, are more likely to exhibit higher levels of digital distraction intensity. On the other hand, this finding suggests that digital distraction intensity can be reduced by increasing cognitive dissonance. If an individual feels emotionally stressed when performing digital distraction behaviors or questions the rightfulness of such behaviors, then he or she will likely refrain from performing digital distraction behaviors. This is consistent with prior studies that suggest that psychological discomfort caused by dissonance would motivate an individual to alleviate the discomfort by modifying their thoughts or behaviors (Fotuhi et al., 2013). In this case, reducing digital distraction intensity serves to alleviate discomfort for individuals who experience higher levels of cognitive dissonance. Therefore, the theory of cognitive dissonance offers a plausible explanation of why individuals' intensity of digital distraction differs and possibly a solution to regulate the intensity by altering the individual's cognitive dissonance levels. In addition, it is observed that both emotional and behavioral dissonance affect digital distraction intensity. This further confirms the multidimensional structure of cognitive dissonance suggested by Sweeney et al. (2000). Behavioral dissonance, which measures the individual's concern about the rightness of the action, shows a slightly stronger relationship with digital distraction intensity than emotional dissonance does. Therefore, to reduce digital distraction intensity, practitioners may need to implement different means of intervention that target different dimensions of cognitive dissonance separately.

Second, our results demonstrate that dissonance against digital distraction can be affected by the level of consonant or rationalizing cognitions. This is consistent with the theory of cognitive dissonance, which suggests the dissonance ratio would determine the magnitude of dissonance (Festinger, 1957; Harmon-Jones & Mills, 2019). This finding indicates that the dissonance one experiences can be effectively manipulated by increasing or reducing the number or importance of consonant or rationalizing cognitions. Interestingly, our results indicate that consonant and rationalizing cognitions have a stronger effect on emotional dissonance than on behavioral dissonance. This may be due to the different resistance to change associated with the two dimensions of cognitive dissonance. As Harmon-Jones and Mills (2019) found, the "resistance to change of a behavioral cognitive element depends on the extent of pain or loss that must be endured and the satisfaction obtained from the behavior" (p. 11). In other words, the more severe the consequences, both positive and negative, the more sensitive the level of behavioral dissonance is to its influencing factors.

Third, this study shows that IA reduces cognitive dissonance by increasing cognitions that are consonant with or rationalize digital distraction. Its components, psychological/emotional conflict, time management issues, and mood modification, significantly increase such cognitions, with the first two having the strongest effects. This finding clarifies how IA influences distraction. While prior studies confirmed IA's impact on distraction intensity (e.g., Chen et al., 2014; Chen et al., 2020; Thomas, 2011; Turel et al., 2011), they did not explain the mechanism. This study suggests that through cognitive dissonance and self-affirmation theory, individuals with IA are more likely to develop cognitions that are congruent with digital distraction behaviors and consequently lead to higher digital distraction intensity.

7. THEORETICAL AND PRACTICAL IMPLICATIONS

The findings of this study offer several significant implications for research in digital distraction and possibly other IS misuse and abuse. First, this study demonstrates the appropriateness of using the theory of cognitive dissonance to understand why individuals' digital distraction intensity varies. In addition to the theoretical paradigms such as reasoned action, planned behavior, and automatic thinking that were employed by prior digital distraction research (Chen et al., 2020; Liberman et al., 2011; Taneja et al., 2015), cognitive dissonance offers another lens through which to develop theories in this area. Furthermore, due to the multitude of applications of the theory of cognitive dissonance in behavioral psychology, the research model validated in this study might be generalized to other types of problematic technology use behaviors. Second, the findings highlight the importance of IA as an antecedent to digital distraction and show how IA distorts individuals' cognitions about problematic technology use behaviors. The conceptualization of the cognitive rationalization process induced by the various dimensions of IA helps shed some light on the reasons for non-compliance behaviors in the face of potentially punitive consequences. Therefore, it is recommended that constructs such as behavioral addiction and cognitive rationalization be incorporated in future technology adoption and use research. Finally, this study contributes to the limited literature on digital distraction and the dark side of IT in general. While the majority of IS research tends to focus on the positive aspects of technology use, there are growing calls to better understand the ineffectual or even harmful uses of technology that are increasingly observed. This area of research is overlooked and understudied; therefore, this study provides important theoretical development and empirical evidence to support future work in this field.

The findings of this study also offer practical implications for educators, especially IS educators, and managers who strive to curb digital distraction in a digitally enabled classroom and work environment, where the student body and workforce are tethered to a multitude of personal and work technologies. First, the research model demonstrates a strong connection between IA and digital distraction, suggesting that understanding an individual's IA level would help predict their likelihood of performing digital distraction behaviors in class or at work. Therefore, practitioners should tackle IA by investing in IA screening, prevention, and intervention to reduce digital distraction intensity in the student body and workforce. In an IS education context, instructors could incorporate self-assessment surveys or discussions about Internet use as part of an IS course. For example, an educator might have students reflect on their own Internet and device usage patterns (using a tool like the Internet Addiction Test) and discuss how excessive use can impede academic success. These exercises are relevant to the IS context in those courses and help prepare future professionals to integrate IS responsibly in the workplace.

Another approach is to increase students' awareness of the negative consequences of digital distraction, thereby strengthening the dissonant cognitions that might dissuade them from indulging in off-task behaviors. For instance, an IS instructor might share research evidence or class data on how multitasking in class lowers grades and comprehension. By making the academic costs of distraction salient, students experience higher levels of cognitive dissonance and are more motivated to discontinue digital distraction behaviors in inappropriate settings. Furthermore, realizing that cognitive dissonance is a multidimensional construct and designing different intervention strategies for targeting emotional and behavioral dissonance could be effective in curbing digital distraction.

Third, because IS education often involves teaching with technology, a practical implication is that instructors should strive to channel students' technology use toward course-related activities. Instead of viewing devices purely as a distraction, IS educators should leverage them as learning tools and turn a potential negative into a positive. A primary rationalization for digital distraction is the need for mental respite from learning or work. Strategies such as active learning, interactive technology-based exercises, and gamification that offer hedonic experiences related to tasks can make it more difficult for individuals to rationalize digital distraction behaviors. For example, an instructor might transform a review session into a competitive quiz game or use a badge system for timely task completion. The overarching principle is to design engaging learning environments that minimize boredom and cognitive overload so that students do not feel the need to "escape" the class via their devices.

8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study has several limitations that may provide directions for future research. First, the focus on synchronous online classes may limit generalizability to in-person courses or remote work. While we believe that the same underlying issues would be found, future studies should test the model in other settings. Second, we did not distinguish among the types of digital distraction (e.g., web surfing, video watching, texting), even though prior research indicates such behaviors may reflect different needs such as boredom or social connection (Seemiller & Stover, 2017). Therefore, future work could examine these distinctions to better understand the motivations and how to curtail them. Finally, the effects of digital distraction may vary by individual characteristics (e.g., gender, age, education, income, culture). Thus, it is recommended that future research projects study the moderating effects of these characteristics in the context of digital distraction.

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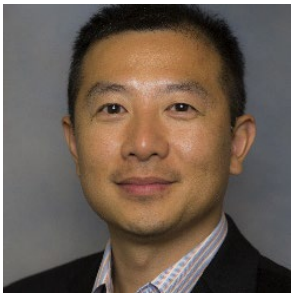

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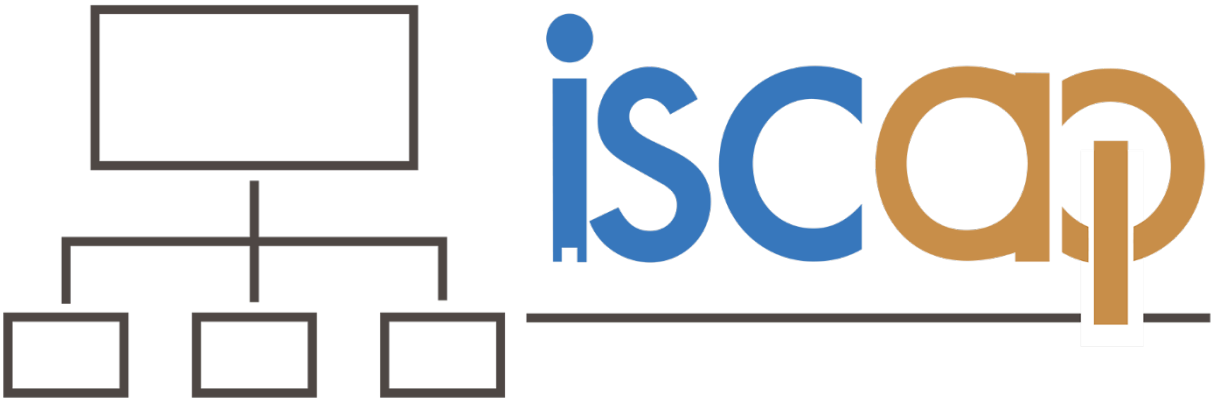

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