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ABSTRACT

Globally, digital distraction is common among young adults, especially university students. This is primarily due to the proliferation of computers, smart phones, and the Internet. While technologies are invaluable in teaching and learning, they can also become an impediment if students use them to engage in activities unrelated to the classwork. Thus, understanding the underlying causes of this behavior in a cross cultural context is highly relevant and desirable. This study, presents a model of in-class digital distraction and using data from 488 U.S., 453 African, and 209 Chinese university students, seeks to identify factors that influence students' in-class digital distraction from a cross-cultural perspective. It posits that the level of in-class digital distraction is impacted by the student's Internet addiction intensity, classroom management issues, instructor/subject characteristics and certain individual factors. The results show that digital distraction is prevalent among university students. Further, the factors influencing the in-class digital distraction differ across cultures. Finally, the paper discusses the implications of the findings both for the researchers and the educators.

INTRODUCTION

The promise of instant communication offered by modern information technologies has created digital distractions that reduce employee productivity and erode workplace etiquette (Rigby, 2006; PR Newswire, 2013). Even education is not immune to this. Information technologies such as laptops, tablets, mobile devices, and the Internet are invaluable tools that on the one hand enhance teaching and learning in the classroom (Maki, Maki, Patterson, & Whittaker, 2000; Saunders & Klemming, 2003; Wen, Tsai, Lin, & Chuang, 2004). But on the other hand, they lead to distraction among students while attending classes. There is substantial empirical and anecdotal evidence that suggests that, globally, university students are prone to use these technologies in class for activities that are irrelevant to the classwork (e.g. playing computer games, emailing and texting, engaging in social networks, surfing the web and shopping online)

– leading to underperformance in learning (Akst, 2010; Burns & Lohenry, 2010; Campbell, 2006; Hefferman, 2010; Rajeshwar, 2010). Studies have shown that cognitive overload and attention distraction caused by non-class-related technology use in the classroom were negatively associated with course performance and self-reported understanding of course material (Fried, 2008; Junco & Cotton, 2011; Kraushaar & Novak, 2010; Martin, 2011; Wurst, Smarkola, & Gaffney, 2008).

As the result, many universities and professors are reacting to this phenomenon by implementing an overall ban on technology use in the classroom (Adams, 2006; Melerdiercks, 2005). Such classroom policies are often deployed without educators' or administrators' full understanding of the underlying causes of why students are drawn to such uses of information technology in the classroom. This is due to the lack of research effort in this area. In fact, there is a paucity of research focused on this issue, and a few prior studies only provide a limited explanation of the motivations behind digital distraction. This paper intends to identify the factors that influence the intensity of in-class digital distraction among university students through an empirical and cross-cultural study. A systematic study on the topic will reveal valuable insights regarding the psychological and cognitive factors behind distractive behaviors as well as structural issues in pedagogy. In addition, cross-cultural comparison of university students from three different regions will offer interesting insights on the impact of culture, economy, and technological infrastructure on digital distraction.

The remainder of the paper is organized as follows. First, as part of the theoretical foundation for this study, the need for a cross-cultural perspective for studying digital distraction among university students is discussed. This is followed by the presentation of the research model of this study and arguments supporting the proposed hypotheses. Next, the research methodology section discusses the measurement development and data collection processes. Data analysis and hypotheses testing results are then presented. This is followed by a discussion of the findings. Finally, the paper concludes by discussing the implications to research and practice, limitations and directions for future research in this area.

THEORETICAL DEVELOPMENT

Cross-Cultural Perspective of Digital Distraction

In addition to identifying the underlying reasons behind in-class digital distraction, this study intends to lend insights into cross-cultural differences in the levels of digital distraction, factors influencing digital distraction and strategies to reduce such distraction among three regions that are vastly different in terms of culture, economy and technological infrastructure: U.S., Africa and China. This objective of the study is also motivated by prior studies that have found that individual behaviors in the context of information technology adoption and use do not universally hold across cultures (e.g. Leidner, Carlsson, Elam, & Corrales, 1999; Srite & Karahanna, 2006; Straub, Keil, & Brenner, 1997). For example, studies have found that national cultures that are risk-averse and high in uncertainty avoidance tend to be less willing to adopt new information technologies; and social norms play a strong role in an individual's technology acceptance behaviors (Jarvenpaa & Leidner, 1998; Thatcher, Srite, Stepina, & Liu, 2003; Srite & Karahanna, 2006). In fact, Hofstede's value dimensions (Hofstede, n.d.) reveal interesting

differences in social and culture perspectives in the U.S., Africa and China. The following table shows the cultural dimension scores for the three regions:

Table 1: Hofstede's Value Dimensions for Africa, China and U.S.

	Individualism	Power Distance	Masculinity	Uncertainty Avoidance	Pragmatism	Indulgence
Africa	27	80	40	45	35	Not Available
China	20	64	66	30	87	24
U.S.	91	40	62	46	26	68

Note that the U.S. subscribes to a high individualism and indulgence and low power distance and pragmatism culture, while both Africa and China demonstrate lower individualism (high collectivism) and power distance cultures. China also displays a very high level of pragmatism and low level of indulgence. In addition, Africa demonstrates relatively low pragmatism. In the context of technology distraction, such notable differences may have implications for the perception about teacher-student relationship (respect of authority), individual needs and/or urges, and competitive behaviors.

Besides Hofstede's value dimensions, other national cultural values such as preference for face-to-face interaction, concept of time, and gender relations also tends to facilitate or impede IT adoption (Hill, Loch, Straub & El-Sheshai, 1998). Other prior studies have also found that IT usage patterns are different across cultures. It has been reported that cultural values help shape how people use IT, the types of IT used, and the outcomes of IT use (Chau et al., 2002; Downing, Gallaugher, & Segars, 2003; Dunn & Dunn, 1989).

In addition to the cultural differences, differences in economic development and technology infrastructure also influence technology use behaviors (e.g. Watson et al., 1997; Yan, Gong & Thong, 2006). World Economic Forum's 2012 Global IT Report (World Economic Forum, 2012) rated 142 countries using the extent to which each country uses information and communications technology (ICT) to enhance their economy and competitiveness. The U.S. is ranked 8th; China 51st, Namibia 105th, and Uganda 110th (Namibia and Uganda are the two African countries included in this study). Further, when ranked according to the ICT penetration and diffusion at the individual level, there are still wide gaps among these countries – rank of 18 for the U.S.; rank of 82 for China; rank of 111 for Namibia; and a rank of 135 for Uganda. However, the business usage index shows a narrower difference with U.S. ranked 10th, China ranked 37th, and Namibia and Uganda ranked 68th and 108th, respectively.

While China and African countries share some resemblance in culture dimensions, there are significant differences in their economies and technology infrastructures. This suggests that there possibly are different patterns of technology distraction among students in the three groups.
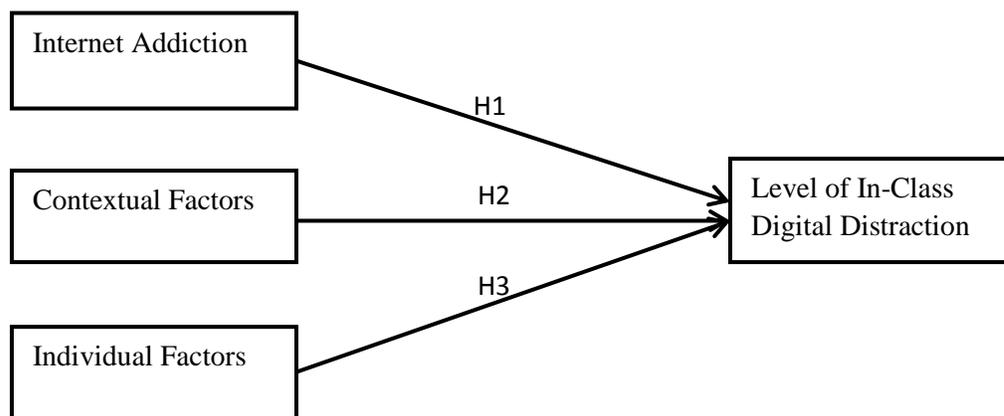
Research Model

While this dual nature of information technology – productive and distractive - has been widely acknowledged and studied in the corporate environment (Davis, Flett, & Besser, 2002; Huang, Wang, Qian, Zhong, & Tao, 2007; Yellowlees & Marks, 2007), research efforts in this area in

the context of higher education have been rather limited. Advocates of technologies in the classroom claim that IT helps engage students, facilitate faculty-student and student-student interactions, and create active learning opportunities (e.g. Driver, 2002; Fitch, 2004; Proserpio & Gioia, 2007). On the other hand, critics argue that much of this research evaluates success via student perceptions (e.g. satisfaction) rather than using objective measures of learning (Fried, 2008). Their research indicates that free access to technologies in the classroom leads to lower student learning outcomes (Fried, 2008; Junco & Cotton, 2011; Kraushaar & Novak, 2010; Martin, 2011; Wurst, Smarkola, & Gaffney, 2008). Somewhat surprisingly, it is reported that access to computers in the classroom has a negative effect on student performance. Actually, students not using any digital technologies in the classroom outperform students that use technology (Martin, 2011; Wood et al., 2012). This underperformance in learning has been attributed mostly to technology-induced distraction when students engage in non-class-related activities (Fried, 2008). Educators and administrators have struggled and achieved little success in finding the right strategies to reduce digital distraction and optimize the positive aspects of technology in the classrooms (Melerdiercks, 2005). Just as the "TV generation" did in the 80's, today's "virtual generation", who grew up in an environment dominated by the Internet, computer games, free information, and impersonal interactivity, are creating paradigm shifts in teaching and learning. These shifts imply that traditional pedagogical principles and approaches need to evolve and adapt to the technology-rich and information-intensive environment (Adams, 2006). This endeavor has to start with a deeper understanding of the root causes of technology-induced distraction in the classroom.

The research model shown in Figure 1 is proposed to examine the factors that influence the level of in-class digital distraction. A thorough review of the digital distraction literature revealed three constructs that might influence university students' in-class digital distraction. The model posits that the level of digital distraction is influenced by the extent of student's addiction to the Internet, individual (e.g., age, gender, time online, multitasking ability, etc.) and contextual (e.g., subject matter, classroom management issues, peer behaviors, not getting caught, etc.) factors.

Figure1: In-Class Digital Distraction Research Model.

Other constructs, for example, technology infrastructure and national culture values, were considered during the construction of the research model. Nevertheless, these constructs are often measured and compared at the national level; therefore, they were not deemed suitable to be included in the current research model, which focuses on the individual level constructs.

Nevertheless, national-level characteristics are considered and deemed helpful in explaining cross-culture differences in digital distraction behaviors found among the three regions. Prior studies have also suggested that environmental attributes such as lighting, temperature and classroom design could be linked to distractive activities (Tesch, Coelho, & Drozdenko, 2011). While these environmental attributes influence in-class distraction in general, they lack direct relevance to digital distraction; therefore, in this study, the authors choose not to include these attributes due to their low content validity in the digital distraction context.

Internet Addiction

Technology addiction, which is exhibited through "an obsessive pattern of IT-seeking and IT-use behaviors that takes place at the expense of other important activities," has become the focus of some IS research (Turel, Serenko, & Giles, 2011, p. 1044). One prominent type of technology addiction, Internet addiction, refers to an excessive and uncontrolled need to use the Internet that has the potential to negatively affect one's effectiveness, health, happiness, and relationships. The symptoms of Internet addiction include salience, withdrawal, conflict, relapse and reinstatement, tolerance and mood modification (Turel et al., 2011). In addition to spending too much time on the Web, problematic Internet use was also found to lead to diminished impulse control, loneliness, depression, distraction, and using the Internet as a tool for social comfort (Davis et al., 2002). This is further confirmed by the study of Razieh et al. (2012) which found that preexisting mental conditions such as anxiety is a significant predictor of Internet addiction among university students. As a social comfort tool, the Internet tends to provide distraction that allows addicts to procrastinate or avoid stressful events, tasks, or thoughts.

The medical community has offered neurobehavioral support for the similarities between Internet addiction and substance addictions. It argues that both addictions result from mental conditions such as diminished impulse control, which, in the case of Internet addiction, is manifested by obsessive cognitions about the Internet and inability to reduce Internet use (Yellowlees & Marks, 2007). Internet addicts have been consistently found to be more impulsive than non-addicts (Saville, Gisbert, Kopp, & Telesco, 2010). In one study, subjects suffering from Internet addiction showed levels of trait impulsivity as high as those exhibited by pathological gamblers suggesting that Internet addiction should be conceptualized as an impulse control disorder (Lee et al., 2012). Furthermore, addiction to the Internet as a medium has been found to lead to compulsive gambling and consumption on the Internet (Turel et al., 2011; Widyanto, Griffiths, & Brunsden, 2011). Prior studies have also found that Internet addiction is a global phenomenon, especially among university students (Frangos, Frangos, & Kiohos, 2010; Huang et al., 2007; Lin, Ko, & Wu, 2011). Technology acceptance and use research assert that Internet addiction leads to inflated perception of the online system and biased reasoning justifying the individual's overuse of the Internet; therefore, researchers recommend that Internet addiction should be incorporated in Internet use studies (Thomas, 2011; Turel et al., 2011). This rationale leads us to believe that digital distractions in the classroom could be partially driven by students' addictive behaviors to technology and the Internet. Therefore, this study proposes that digital distraction is partially caused by uncontrollable impulsive behaviors exhibited by Internet addiction. We argue that one's Internet addiction level affects the level of digital distraction exhibited in the classroom.

Hypothesis 1: Internet addiction positively influences a university student's in-class digital distraction intensity.

Contextual Factors

Prior studies have suggested that an individual's beliefs about information technology, which has been shown to impact subsequent technology use behaviors, were influenced by the institutional and social context in which the individual interacts with information technology (Agarwal, 2000; Lewis et al., 2003). Institutional factors such as organizational and management commitment and support and facilitating conditions and social factors such as peer pressure have been consistently found to influence technology use behaviors (Venkatesh & Davis, 2000; Venkatesh et al., 2003; Lewis et al., 2003). Furthermore, prior studies have also indicated that work environment factors such as overload and autonomy influence individuals' innovative behaviors when using information technologies (Ahuja and Thatcher, 2005). Therefore, the importance of contextual factors in determining individuals' technology use behaviors is irrefutable. In the education domain, the role that contextual factors play in classroom learning behaviors is also emphasized. Factors such as classroom environment, instructor behaviors, and instructional methods have been repeatedly found to influence classroom behaviors and learning outcomes (Young et al., 2003; Finn & Pannozzo, 2004; Ahmad et al., 2013).

More specifically to this study, classroom distraction literature suggests that distractions are caused by environmental factors, instructor characteristics/behaviors, peer behaviors, and learner characteristics (Tesch et al., 2011). For example, in courses that deal with theoretical subjects (e.g. calculus and physics), it is often difficult to keep student attention unless the professor is very engaging and entertaining. The student's lack of interest in the subject may also result in a higher level of digital distraction. Student concentration is affected when there are no curbs imposed on the student use of digital technologies in the classroom and others in class are engaged in distractive activities (Campbell, 2006; Gilroy, 2003). Obviously, the lack of concentration contributes to unsatisfactory learning environments and poor performance (Seidman, 2005). Additionally, some studies have also suggested that the majority of today's college students, labeled the "net generation" or "digital natives", are sensing, visual, active and global learners; therefore, a mismatch between student learning preference and instructional and classroom management approaches may be a key contextual factor behind in-class digital distraction (Adams, 2006; Guthrie, 2014). Based on this rationale, this study posits that contextual factors such as the subject matter, fellow student behavior, dullness of the lecture, and classroom management influence the intensity of in-class digital distraction.

Hypothesis 2: The contextual factors influence a university student's in-class digital distraction intensity.

Individual Factors

The impact of individual factors on information technology related behaviors has long been studied in IS research. Studies have found that demographic factors such as age, gender, and experience influenced information technology use behaviors (Venkatesh & Morris, 2000; Venkatesh et al., 2003). Drawing from culture research, IS studies have concluded that men's

technology use intention and behaviors were more influenced by performance expectation while technology use of women, older workers and workers with limited experience were more influenced by effort expectancy and social influence (Venkatesh et al., 2003). Prior digital distraction literature has also acknowledged the impact of personal characteristics on digital distraction behaviors in the classroom. For example, Tesch et al. (2011) found that female university students reported higher levels of in-class distraction than male students, and they also found that graduate students were significantly less distracted than the undergraduate students.

Besides demographic characteristics, individuals' cognitive factors such as computer self-efficacy and personal innovativeness have also been found to influence technology use behaviors (Lewis et al., 2003). While to the best of our knowledge, no prior studies have linked cognitive constructs to digital distraction, we found perceived multitasking ability to be especially relevant in this context. Multitasking, a byproduct of a digital society, has received significant research attention from both psychology and education. While multitasking gives the learner the illusion of accomplishing more in less time, empirical studies have found that it contributed to decrease in concentration, cognitive abilities, accuracy and productivity among students (Foerde, Knowlton, & Poldrack, 2006; Kraushaar & Novak, 2010; Rubenstein, Meyer, & Evans, 2001). Fried (2008) reported that higher laptop use in the classroom led to an increase in multitasking and distraction. Kraushaar and Novak (2010) define these "tasks or activities where cognitive resources are used to process information that is not directly related to the course material" as distractive multitasking. It is reasonable to assume that students who are more confident in their multitasking abilities tend to engage in these distractive multitasking more frequently. Therefore, our study proposes that individual factors such as age, gender, year of study, time spent online and perceived multitasking ability act as influencers of digital distraction in the classroom.

> **Hypothesis 3: The individual factors influence a university student's in-class digital distraction intensity.**

RESEARCH METHODOLOGY

Questionnaire

A questionnaire consisting of three sections was designed. The questionnaire items were generated based on an extensive literature review of how previous research had measured the constructs used in this research. First section of the questionnaire consisted of 20 items developed by Young (1998) to assess Internet addiction. In this Internet Addiction Test (IAT), each item is measured using a 5-point Likert scale (1 = Never; 5 = Very Frequently). The IAT has been validated and tested for psychometric properties (Davis et al., 2002; Widyanto & McMurran, 2004; Widyanto et al., 2011) and also validated in numerous cultural contexts – thus, making it especially suitable for cross-cultural studies (Khazaal, et al., 2008; Kesici & Sahin, 2010). According to Widyanto and McMurran (2004), there are three underlying dimensions to Internet addiction and they are named as: emotional/psychological conflict; time management issues; and mood modification. Table 2 shows these twenty items and the three underlying factors.

Table 2: Internet Addiction Items.

1. Do you prefer the excitement of the Internet to intimacy with your friends or family?
2. Do others in your life complain to you about the amount of time you spend online?
3. Does your job/school performance or productivity suffer because of the Internet?
4. Do you become defensive or secretive when anyone asks you what you do online?
5. Do you block disturbing thoughts about your life with soothing thoughts of the Internet?
6. Do you find yourself anticipating when you will go online again?
7. Do you try to cut down the amount of time you spend online and fail?
8. Do you try to hide how long you've been online?
9. Do you choose to spend more time online over going out with others?
10. Do you find that you stay online longer than you intended?
11. Do you neglect household chores to spend more time online?
12. Does your work suffer (e.g. postponing things, not meeting deadlines, etc.) because of the amount of time you spend online?
13. Do you check your e-mail before something else that you need to do?
14. Do you find yourself saying "Just a few more minutes" when online?
15. Do you form new relationships with fellow online users?
16. Do you fear that life without the Internet would be boring, empty, and joyless?
17. Do you snap, yell, or act annoyed if someone bothers you while you are online?
18. Do you lose sleep due to late-night log-ins?
19. Do you feel preoccupied with the Internet when off-line, or fantasize about being online?
20. Do you feel depressed, moody, or nervous when you are off-line, which goes away once you are back online?

Internet Addiction Factors:

Emotional/Psychological Conflict	Items 1-9
Time Management problems	Items 10-14
Mood Modification	Items 15-20

Items in the second part of the questionnaire were crafted to assess the extent to which a student is distracted by technology in the classroom. Each student provides their overall perceptions regarding technology-enabled distraction in classes over the previous six months as opposed to asking the student to focus on just one specific class. This approach, we felt, would provide a holistic perspective on student distractions and would encompass a variety of classes. However, it may still be revealing to focus on just one class if the main purpose of the research is to determine digital technology distraction in one instructor's class, or in one subject. We leave this for future studies. The distraction level of a student was measured using six items - five items focused on specific digital distraction activities, e.g., surfing the web, gaming, visiting social networking sites, e-mail, and text messaging; and the last item assessed the overall distraction level and also served as a check for consistency in responses. Again, each item was measured using a 5-point Likert scale (1= never; 5 = very frequently).

The third section of the instrument was designed to ferret out potential reasons for non-class-related technology use. The first part of this section included 11 items that were used to evaluate

the impact of contextual factors on technology distraction. The second part asked respondents to provide demographic information such as gender, age, school year, daily time spent online, and perceived multitasking ability to assess the impact of individual factors on technology distraction.

The questionnaire was pilot tested among a small number of faculty and students for improving its understandability, readability and comprehensiveness. Several items, particularly those dealing with the measurement of distractive behaviors and their causes, were modified based on the feedback. Since the scale for Internet addiction is well established, it was left unchanged.

Data Collection

Data for this study were collected during 2012 and 2013 from university students in Africa (Namibia and Uganda), China, and the United States. In all universities, a number of classes across campus were chosen in order to cover a wide spectrum of majors, students and courses. Students were asked to complete the questionnaire online, they were assured of its confidentiality, and they were told that their responses should reflect general in-class behaviors related to digital technologies and do not necessarily have to pertain to the class they were attending. The following table shows the number of universities and the number of usable questionnaires in each of the three regions.

Table 3: Data Collection.

Region	# Universities	n
Africa	3	453
China	1	209
United States	2	488

RESULTS

Sample Profile

Table 4 shows the profiles of the respondents. There are significantly more male students then female students in the China sample: 74.2% versus 25.8%. However, in the Africa and the U.S. samples, these figures are not that lopsided even though the percent of male students exceeds that of female students. With respect to age, in the China sample, all students are under twenty-five years of age. The percent of students who are 25 or older in the African and the U.S. samples are 15% and 11%, respectively.

Table 4: Sample Profile.

	Africa (n =453)		China (n=209)		U.S. (n=488)	
	n	%	n	%	n	%
Gender						
Male	242	53.4%	155	74.2% `	279	57.2%
Female	211	46.6	54	25.8	209	42.8

Age						
Under 20	95	21.3	40	19.1%	82	16.8%
20 and under 22	209	46.9	113	54.1	280	57.3
22 and under 25	76	17.0	56	26.8	75	15.3
25 and under 30	36	8.1	0	0	31	6.3
Over 30	30	6.7	0	0	21	4.3
School Year						
First Year	151	33.9	30	14.4%	8	1.6%
Second Year	160	36.0	59	28.2	109	22.3
Third Year	88	19.8	82	38.2	252	51.5
Fourth Year	39	8.8	38	18.2	111	22.7
Masters	7	1.6	0	0	9	1.8
Average Daily Time Spent online						
Less than 15 minutes	75	16.7	2	1.0%	4	0.8%
15 and under 30 minutes	76	16.9	5	2.4	25	5.1
30 and under 60 minutes	108	24.0	42	20.3	91	18.6
1 hour and under 2 hours	101	22.4	71	34.3	174	35.5
2 hours and under 4 hours	49	10.9	63	30.4	135	27.6
Over 4 hours	41	9.1	24	11.6	61	12.4
Multi-Tasking Effectiveness						
Not effective at all	15	3.4	17	8.3%	18	3.7%
Somewhat Effective	27	6.0	103	50.0	100	20.5
Effective	139	31.1	75	36.4	194	39.8
Very Effective	198	44.3	10	4.9	131	26.8
Extremely Effective	68	15.2	1	0.5	45	9.2

Further in all samples, the overwhelming percent of the students are undergraduate students (98.4% in Africa, 100% in China, and 98.2% in the U.S.). With respect to daily time spent online, patterns of usage are similar in China and the U.S.: close to 40% spend over two hours online, and a very small percent of students spend less than 30 minutes online. On the other hand, in the African sample, nearly one-third of the students report spending less than 30 minutes a day online and only one in five spend over two hours. Clearly, students in Africa spend considerably less time online than their counterparts in both China and the U.S, possibly due to more limited access to technologies. Close to 60% of the African students rate themselves as being "very effective" to "extremely effective" at multitasking. But these figures are only 36% for the U.S. and 5.4% for the Chinese students.

Internet Addiction

An overall Internet addiction score is calculated by averaging the responses to the 20 IA items (Table 2). In addition, the scores for the three underlying factors of IA are computed by simply averaging those items that comprise the factor. Widyanto et al. (2011) have further suggested classifying individuals into groups according to the intensity of their addiction using the overall Internet addiction score. These groups are defined as follows:

Average online user   Overall IA score between 1.00 and 1.95

Frequent problems with Internet use   Overall IA score between 2.00 and 3.45
Significant problems with Internet use.   Overall IA score between 3.50 and 5.00

The first panel of Table 5 shows a summary of the overall Internet addiction and the mean and standard deviation of the underlying IA factors for the three groups of students. Note that students in Africa exhibit significantly higher Internet addiction (2.42) compared to the students in China (2.25) or the U.S. (2.28). Also, the Chinese and U.S. students' average addiction scores are not significantly different. On "psychological/emotional conflict" dimension of IA, the three groups are similar. The U.S. students show significantly higher problems with "time management" (2.80) than the students in China and Africa (scores of 2.53 2.62, respectively). Finally, with respect to leaning on the Internet for "mood modification", the three groups are significantly different with students in Africa having the highest score (2.46), followed by Chinese students (2.12) and the U.S. students (1.98). Next, to see if the mean Internet addictions differ for the three groups, a series of Analysis of Variance (ANOVA) and post-hoc tests are performed. The second panel of Table 5 summarizes these results. In this table, countries listed within parentheses have similar average scores while countries belonging to separate groups have statistically significantly different average addiction scores.

Next, the third panel of the table shows the distribution of students in each of the three IA groups. Note that a little over 60% of the students exhibit frequent problems with the Internet use across all samples and the percent of students with significant problems is 5.9% in Africa, 1.9% in China, and 4.3% in the U.S. It is also worth noting that nearly one-third of the students in each sample are average online users. Thus, Internet addiction among college students is fairly persistent and serious.

Table 5: Mean (SD) of Overall Internet Addiction (IA) and Dimension of Internet Addiction.

	Africa	China	U.S.
Overall IA Score	2.42(0.71)	2.25(0.57)	2.28(0.64)
IA Factors			
Psychological/Emotional Conflict	2.28(0.74)	2.18(0.60)	2.20(0.66)
Time-Management Problems	2.62(0.86)	2.53(0.75)	2.80(0.82)
Mood Modification	2.46(0.96)	2.12(0.64)	1.98(0.74)

Analysis of Variance (ANOVA) Results

	F	p	Similar Groups
Overall IA Score	6.92	.001[*]	{Africa},{China, U.S.}
Psychological/Emotional Conflict	2.23	.109	{Africa, China, U.S.}
Time-Management Problems	9.93	.000[*]	{Africa, China}, {U.S.}
Mood Modification	41.39	.000[*]	{Africa},{China}, {U.S.}

*significant at the .05 level

Percentage Distribution across IA Groups

IA Group	Africa	China	U.S.
Average online user	29.6%	32.1%	34.4%
Frequent problems due to Internet use	64.5	66.0	61.1
Significant problems due to Internet use	5.9	1.9	4.3

Digital Distractive Activities

To assess the extent to which digital distractive behavior was occurring in the classroom, each student reported the level of their distractive activities such as surfing the web, playing computer/mobile games, visiting social networking sites, checking/sending e-mails, and reading/sending text messages. This was measured by using a 5-point Likert scale (1 = never; 5 = very frequently). Further, each student was asked to indicate their overall distractive digital use in class using the same scale. Table 6 shows the percent of students who frequently or very frequently engaged in each activity. First, across all three samples texting, checking social networking sites, and surfing the web turn out to be the top three distractive activities. However, the patterns and frequency of activities varied according to where the students are from. For instance, 52% of the Chinese students report checking social networking sites and 50% indicate surfing the web. For the U.S. students these figures are 31% and 32%, respectively. For African students, these numbers are still lower: 27% and 17%, respectively. For text messaging, differences among the three samples are not that pronounced: 31% in Africa; 32% in China; and 31% in the U.S. The average of the overall distraction scores is also reported in Table 6 with China with a mean score of 3.07 followed by the U.S. with a mean of 2.94 and then Africa with a mean of 2.76. To see if these means are statistically significantly different, Analysis of Variance revealed differences at the .05 level (F = 4.60; p = .01). Post hoc tests further showed that the mean distraction scores for China and the U.S. are not different but Africa's mean is statistically significantly lower than those of China and the U.S.

Table 6: Percent of Students "Frequently" or "Very Frequently" Engaged in a Digital Distractive Activity and Mean Digital Distraction Scores.

Activity	Africa (n = 457)	China (n = 210)	United States (n = 494)
• Surf the Web	16.9%	50.0%	31.5%
• Play computer/mobile phone games	9.3%	14.2%	8.5%
• Check social networking sites	27.2%	52.1%	31.2%
• Check/write e-mails	14.9%	3.8%	22.9%
• Read/send text messages	31.1%	32.9%	35.0%

A 5-point scale is used (1=never; 5 = very frequently) to measure the intensity of each distractive activity.

Mean digital distraction score	2.76	3.07	2.94

Contextual Factors

In order to identify the key contextual factors (e.g. classroom/subject and instructor traits) that could conceivably affect students' behavior in class, eleven items dealing with class environment, teacher and subject traits were developed. Each student was asked to rate their agreement/disagreement with each item as a reason to engage in distractive behavior. Here a five-point agreement/disagreement scale was used (1-strongly disagree; 5=strongly agree). Table 7 shows the items, their means and standard deviations. To further examine these variables, an examination of the correlations revealed that there are significant inter correlations among these variables. Thus, to identify underlying factors (constructs), a factor analysis was performed and it resulted in identifying two factors: *Classroom Management Issues* and *Instructor/Subject Characteristics.* Details regarding this analysis and identification of these two factors are available in Nath et al. (2014)*.* Table 7 shows these factors as well as the mean (SD) of the two factors for the three groups of students.

Table 7: Mean (Standard Deviation) of Possible Reasons for Distractive Computer/Mobile Phone Use.

Factor	Africa	China	United States
Classroom Management Issues	2.29(0.93)	2.57(0.84)	3.11(0.92)
I see other students doing it	1.80(1.16)	2.78(1.13)	2.90(1.21)
The instructor is not likely to see what I am doing	2.22(1.27)	2.42(1.04)	3.01(1.16)
The instructor does not seem to care	2.35(1.38)	2.72(1.18)	3.26(1.23)
The delivery method of the class is primarily lecture	2.36(1.35)	2.49(1.11)	3.09(1.18)
Computer/mobile phones are allowed to be used in the class	2.57(1.48)	2.55(1.14)	3.25(1.21)
The class size is large enough for me to remain anonymous	2.45(1.50)	2.41(1.10)	3.14(1.18)
Instructor/Subject Characteristics	2.23(1.05)	3.43(0.95)	3.16(1.03)
The instructor's lecture is not engaging	2.56(1.41)	3.83(1.11)	3.35(1.23)
I do not like the instructor	1.75(1.20)	3.30(1.26)	2.81(1.24)

I do not like the subject of the class	1.97(1.25)	3.43(1.22)	3.06(1.13)
The subject of the class is not challenging	2.35(1.39)	2.94(1.16)	3.24(1.15)
The subject of the class is boring	2.47(1.43)	3.64(1.14)	3.33(1.18)

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*A 5-point agreement scale is used (1=strongly disagree; 5 = strongly agree); numbers in parentheses are the standard deviations.

Explaining Digital Distraction

To identify variables that explain students' digital distraction in class, Ordinary Least Squares (OLS) regression analyses were performed – one for each group of students. Explanatory variables considered included Internet addiction, student demographic variables, and two underlying factors derived from a collection of reasons for digital distraction. A brief description of the variables considered follows:

Dependent Variable:

Distraction score - This is the score of the item, "How often did you use the computer/mobile phone for any activities that were not relevant to the class during a class in the past six months?" It is measured using a 5-point Likert scale (1 = never; 5 = very frequently).

Explanatory Variables:

- Internet Addiction (IA) score
- *Classroom Management Issues* factor – It is measured as the average of the six items.
- *Instructor/Subject Characteristics* factor – It is measured as the average of the five items.
- Gender (0=male; 1=female)
- Age - It is measured as a categorical variable (1 = under 20; 2 = 20 and under 22; 3 = 22 and under 25; 4 = 25 and under 30; 5 = 30 or over).
- Time online – it measures the total time spend online on a typical day.
- Multi-tasking effectiveness - It is measured on 5-point Likert scale (1=not effective; 2 = somewhat effective; 3 = effective; 4 = very effective; 5 = extremely effective).

To check for the multicollinearity problems in regression analysis, a commonly used measure for tagging collinear variables is the variance inflation factor (VIF[1]) (Myers, 1986). VIF of a variable shows the extent to which the variance of the regression coefficient estimate is inflated due to the existence of multicollinearity. As a rule of thumb, if the VIF of an independent variable exceeds 10, the variable is considered highly collinear and it becomes a candidate for exclusion from the regression model (Kleinbaum, Kupper & Miller, 1988). In our analyses, none of the VIF values exceeded the threshold of 10 and thus, there was no evidence of multicollinearity. In light of the cultural and technological difference among the groups of students in Africa, China and the U.S., it is recommended that separate regression analysis be performed on each group of students. Step-wise regression analysis was performed to identify key explanatory variables. Table 8 shows the results of these regression analyses.

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[1] $VIF_j = 1/(1 – R^2_j)$ where R^2_j is a measure of the degree of multicollinearity between X_j and other explanatory variables. Therefore, if $R^2_j = 0$, then $VIF_j = 1$, and if $R^2_j = 1$, then $VIF_j = \infty$.

Table 8: OLS Regression Analysis Results by Groups.

Africa

Variable	Unstandardized Regression Coeff.	Standardized Regression Coeff.	Standard Error	t	p
Constant	1.123	--	0.258	4.36	.000
Student Age	-0.128	-0.098	0.058	-2.22	.027
Gender	0.339	0.117	0.126	2.70	.007
Time online	0.108	0.113	0.043	2.53	.012
Classroom Management issues	0.297	0.192	0.083	3.57	.000
Instructor/Subject Characteristics	0.343	0.249	0.258	4.53	.000

Dependent variable: Y = Digital Distraction
Adjusted R^2 = 0.21, F = 24.05; p = .000

China

Variable	Unstandardized Regression Coeff.	Standardized Regression Coeff.	Standard Error	t	p
Constant	1.262	--	0.323	3.91	.000
Classroom Management issues	0.346	0.264	0.090	3.84	.000
Instructor/Subject Characteristics	0.421	0.363	0.080	5.29	.000

Dependent variable: Y = Digital Distraction Intensity
Adjusted R^2 = 0.310, F = 31.16, p = .000

U.S.A.

Variable	Unstandardized Regression Coeff.	Standardized Regression Coeff.	Standard Error	t	p
Constant	-0.076	--	-0.388	0.70	.698
Internet Addiction	0.302	0.423	0.072	4.20	.000
Classroom Management issues	0.554	0.423	0.072	7.74	.000
Instructor/Subject Characteristics	0.193	0.165	0.062	3.10	.002

Dependent variable: Y = Digital Distraction
Adjusted R^2 = 0.380, F = 99.78; p = .000

Combined

Variable	Unstandardized Regression Coeff.	Standardized Regression Coeff.	Standard Error	t	p
Constant	1.013	--	0.173	5.84	.000
Internet Addiction	0.231	0.117	0.052	4.43	.000
Student Age	-0.134	-0.101	0.035	-3.85	.000
Classroom Management issues	0.315	0.241	0.046	6.90	.000
Instructor/Subject Characteristics	0.281	0.248	0.039	7.17	.000

Dependent variable: Y = Digital Distraction
Adjusted R^2 = 0.266, F = 100.94; p = .000

Note that all three models are statistically significant at the .01 level as indicated by the F statistics (shown below each panel in Table 8). In addition, adjusted R^2, a measure of the proportion of variation in digital distraction explained by the explanatory variables, varies from 0.21 for Africa to 0.38 for the U.S. and, with China having a value of 0.31.

Two variables *"Classroom Management Issues"* and *"Instructor/Subject Characteristics"* are common across all three regression models. For China, these are the only two variables that are significant in explaining digital distraction. However, in the U.S. sample, these two variables plus Internet addiction are found significant. Further, the regression model for Africa contains five variables: Age, gender, time spent online, Classroom management issues, and Instructor/Subject characteristics. Thus, it appears that for the three groups of students, there are some commonalities among the determinants of in-class distraction but there exist some differences as well.

The two common variables for all three models, *"Classroom Management Issues"* and *"Instructor/Subject Characteristics,* have positive influence on distraction in that a mismanaged class environment and the perception of an unengaging subject and instructor are both drivers of increased digital distraction by students. Therefore, improvements in areas that underpin these two contextual variables are critical in controlling student distraction. For the U.S. sample, addiction to the Internet is of concern as the regression coefficient associated with this variable is positive in sign. In the African sample, student age has negative regression coefficients indicating that older students are less prone to digital distraction compared to their younger counterparts. Also, in Africa, gender of the student is a significant variable in determining digital distraction. Consistent with findings of prior studies, female students exhibit significantly higher digital distraction than the male students (mean distraction scores: Males = 2.58; females = 2.96, t = -2.81; p = .005) (Tesch, et al., 2011). Finally, for African students, the more time they spend online, the higher their digital distraction.

Next, in order to identify important variables from the combined data, regression analysis shows four variables as significant: Internet addiction, age, classroom management issues, and instructor/subject characteristics. The combined model has an adjusted R^2 of 0.27 and is statistically significant (F = 100.94; p = .000). Hypothesis testing results are displayed in Table 9.

Table 9: Hypothesis Testing Results.

Models	Hypotheses	Results
Africa	Hypothesis 1 (Internet Addiction → In-Class Digital Distraction Intensity)	Not Supported
	Hypothesis 2 (Contextual Factors → In-Class Digital Distraction Intensity)	Supported
	Hypothesis 3 (Individual Factors → In-Class Digital Distraction Intensity)	Supported
China	Hypothesis 1 (Internet Addiction → In-Class Digital Distraction Intensity)	Not Supported
	Hypothesis 2 (Contextual Factors → In-Class Digital Distraction Intensity)	Supported
	Hypothesis 3 (Individual Factors → In-Class Digital Distraction Intensity)	Not Supported
U.S.A.	Hypothesis 1 (Internet Addiction → In-Class Digital Distraction Intensity)	Supported
	Hypothesis 2 (Contextual Factors → In-Class Digital Distraction Intensity)	Supported
	Hypothesis 3 (Individual Factors → In-Class Digital Distraction Intensity)	Not Supported
Combined	Hypothesis 1 (Internet Addiction → In-Class Digital Distraction Intensity)	Supported
	Hypothesis 2 (Contextual Factors → In-Class Digital Distraction Intensity)	Supported
	Hypothesis 3 (Individual Factors → In-Class Digital Distraction Intensity)	Supported

DISCUSSION OF RESULTS

The primary objective of this cross-cultural study is to identify factors that contribute to in-class digital distraction by university students. Based on data collected from African, Chinese, and the U.S. students, overall, the results show that digital distraction intensity is influenced by a student's Internet addiction level and individual and contextual characteristics. Even though the sets of variables associated with digital distraction are not the same across the three groups of students, there are many commonalities. Table 10 summarizes and identifies the significant variables within each group as well as for the combined group.

Table 10: Explanatory Variables and their significances in Regression Analysis.

Variable	Africa	China	U.S.	Combined
• Internet Addiction	ns	ns	+	+
• Gender	+	ns	ns	ns
• Age	-	ns	ns	-
• Multi-tasking effectiveness	ns	ns	ns	ns
• Time online	+	ns	ns	ns
• *Classroom Management Issues* factor	+	+	+	+
• *Instructor/Subject Characteristics* factor	+	+	+	+

ns: not significant
+: Positive impact on Distraction
-: Negative impact on Distraction

These findings offer important insights regarding the determinant of digital distractions and possible mitigating strategies. For the combined data, Internet addiction is found to be a key predictor of digital distraction. Prior studies have associated IA with impulsivity, which likely contributes to an uncontrollable urge to engage in digital distraction. While educators do not have much control over students' Internet addiction, instructors' awareness of this phenomenon can be instrumental in crafting classroom management strategies. Among the individual characteristics, student age - usually associated with maturity and self-control, is negatively associated with digital distraction, i.e., the older the student, the lower the digital distraction. Finally, both contextual factors - classroom management issues and instructor/subject characteristics - influence distraction. First, in-class digital distraction goes up when the instructor tolerates and fail to control technology abuse, other students engage in this behavior, and the class size is large enough to provide anonymity. This finding underscores the importance of proper classroom management strategies in influencing digital distraction tendencies. Second, instructor/subject characteristics, such as boring subject matter, unengaging lectures, and not liking the subject matter, result in more pronounced digital distraction. This implies that some structural issues may exist in today's education. As Adams (2006) points out that many students are raised in an environment dominated by a variety of fast-paced information feed channels and as such they unrealistically expect, from instructors, infotainment - which integrates entertainment and the information-sharing aspect of education. Yet these students often fail to distinguish what is relevant from what is entertainment.

Our findings suggest that multi-faceted approaches are needed to effectively reduce digital distraction and make information technology a valuable tool for education. First, to minimize digital distraction in the classroom, Internet addiction needs to be managed and reduced. Steps to help students manage and reduce Internet addiction will yield a wide range of positive changes in cognition and behaviors besides reduction in digital distraction (Christakis et al., 2011; Hamade, 2009; Kittinger, Correia, & Irons, 2012; Zhang, Clinton, & McDowell, 2008). Second, strategies for improving teaching via better delivery approaches should be investigated by educators. Disengaging lectures was cited as the number 1 reason for both U.S. and Chinese students and number 2 reason for African student for in-class digital distraction. This finding reflects that a

severe misfit between the prevailing instructional approaches and student learning preferences exists in university classrooms. Today's university students tend to be sensing, visual, active and global learners who likely respond well to instructional strategies such as demonstration and hands-on experience, small-group brainstorming activities, and team learning exercises and learn best when the instructor is able to demonstrate the relevance of course materials to other knowledge and real world experience (Adams, 2006; DeFrene et al., 2009; Graf et al., 2007). Also, given the fact that students tend to demonstrate diverse learning preferences, it is suggested that increasing the variety of instructional methods may not only limit digital distraction but also improve the quality of instruction and student learning and engagement. Instructors should be provided training to take advantage of the media-richness and interactive features of IT in teaching. Concole et al. (2004) have developed a model that purports to support varying teaching approaches in a technology-rich environment. In the absence of a well-planned training strategy on the part of university administrators, technology-course integration efforts are likely to be sub-optimal and not propagate throughout the university.

Third, individual characteristics of target students should be understood by the instructors to prepare themselves for possible classroom management issues they would face. Some of the top reasons for engaging in distractive behaviors in class cited by students include "computer/mobile phones are allowed in the class" and "the instructor does not seem to care." Thus, policies regarding digital devices in the classroom should be communicated to students and strictly enforced to discourage distractive activities. Actually, it is quite possible that digital distraction may be a "crime of opportunity," – the students do it as the technology is right there. While a blanket ban on digital devices may not be advisable or even practical, there is an urgent need for developing and enforcing a code of conduct that clearly states the expectations with respect to the use of IT in the classroom. For it to be practical and equitable, the policy needs to be consistent across the departments, colleges, or even university as leaving the development and enforcement of such a policy to individual instructors is impractical and may be confusing to students. Digital distraction policies may also become an integral part of the information provided to students upon on their enrollment at the university. As enforcers of the policy, instructors must carry out the policy consistently and take charge to maintain a professional classroom environment where students understand the code of conduct and are refrained from engaging in digitally distractive activities.

Cross-cultural comparisons reveal some interesting findings. Internet addiction is more pronounced in Africa (IA score of 2.42) compared to the U.S. (2.28) and China (2.25), despite the fact that access to the Internet is much more limited in Africa than in the U.S. or China. In particular, U.S. students suffer more time-management problems than their African and Chinese counterparts. A plausible explanation for this may be that U.S. students have the easiest and least expensive access to the Internet. African students lean on the Internet for mood modification more so than the students in China and the U.S.. This suggests that the problem of Internet addiction is not restricted to regions with high availability of technological infrastructure only. It further implies that Internet addiction is not reflected by spending too much time online only as African students on average reported spending much less time online than U.S. and Chinese students did in this study. Instead, emotional dependency on the Internet is likely a more important and reliable indicator of addiction to the Internet.

With respect to digital distraction, texting is the most dominant activity for African and the U.S. students while it comes in third for the Chinese students. Social networking is the most frequent distractive activity for students in China, and it comes in second for the African and third for the U.S. students. Surfing the web shows up second for the U.S. and Chinese students. Overall, however, students in China have the highest mean digital distraction score (3.07) as opposed to the U.S. (2.94) and Africa (2.76). Despite a higher level of Internet addiction, digital distraction score is lower among African students. This may be due to relatively low level of technology adoption and the paucity of technology infrastructure in Africa compared to that in the U.S. and China. This is further affirmed by the average time students spend daily online. Nearly fifty-seven percent of African students report spending less than an hour online per day. These figures for China and the U.S. are 24% and 25%, respectively. Thus, it is reasonable to expect the intensity of digital distraction to increase among African students as facilitating information technologies become more available. Furthermore, this finding suggests that cross-cultural comparison of digital distraction intensity would be more meaningful when the context of technological infrastructure is considered.

What might be the reasons for Chinese students to have higher levels of digital distraction compared to their counterparts in Africa and the U.S.? One possible explanation points to the comparably younger age of the students – none is over 25. Whereas in Africa and the U.S., these figure are about 15% and 12%, respectively. This is in line with the findings of this study and prior studies that indicate younger students are typically more distracted in the classroom (Tesch et al., 2011).

Comparison among the three regression models for the three countries reveals interesting cross-cultural differences in terms of the causes of in-class digital distraction. Among the three country models, the U.S. model was the only one that confirms a strong relationship between Internet addiction and digital distraction intensity. According to the Hofstede national culture dimensions, U.S. displays relatively weak control over their desires and impulses with an indulgence score of 68 compared to a low indulgence score of 24 found in the Chinese culture. Therefore, it can be concluded that the effect of Internet addiction diminishes or is better controlled through the cultural tendency of not indulging one's impulses.

While classroom management issues was found to influence digital distraction intensity in all the models, its standardized regression coefficient is much higher in the U.S. model (0.423) compared to the rest of the models (China: 0.264; Africa: 0.192; Combined: 0.241). National cultural difference may help explain the relative importance of classroom management issues in the U.S. context. High power distance and low individualism displayed in the Chinese and East African cultures might have led to a deeper and innate respect of authority and well-controlled suppression of individual needs and urges in the classroom among university students in these countries. Therefore, Chinese and African students are more likely to comply with the expectation of low distraction tolerance in the classroom regardless of whether their instructors were actively enforcing classroom policies or not. U.S. students who display low power distance and high individualism culturally, on the other hand, only tend to refrain from digital distraction when their instructors enforce classroom policies of low distraction tolerance strictly and explicitly.

Extremely high pragmatism displayed in the Chinese culture may contribute to the relatively high importance of Instructor/Subject Characteristics factor with a regression coefficient of 0.363 in the Chinese model compared to 0.165 in the U.S. model. As Hofstede claimed, individuals in a highly pragmatic culture believed that truth depended very much on the situation. The Chinese model suggests that Chinese students adjust their digital distraction intensity mostly based on their perception about the instructor and subject matter. By the same token, low pragmatism in the U.S. culture may explain the relatively low importance of this factor in the U.S. model. These findings further underscore the importance of taking national culture differences into consideration when studying digital distraction.

IMPLICATIONS, LIMITATIONS AND CONLCUSION

There are several implications of these findings for both researcher and educators. This study makes a contribution to the understanding of why students engage in in-class digital distraction from a cross-cultural perspective. While there has been some published research that examines the challenges of digital distraction, only a limited number of studies have delved into the motivations behind these distractive behaviors. This study attempts to fill the void in current literature by identifying the factors that influence in-class student digital distraction. This research also offers researchers a starting point to further investigate the root causes and potential impacts of digital distraction.   The cross-cultural comparison suggests that while the phenomenon is global, the reasons behind digital distraction may vary according to different cultural, technology environment, and economic conditions.   This finding should motivate further cross-cultural studies in this area.

From the practical perspective, this study confirms that in-class digital distraction is prevalent and global. While the findings about the relationship between information technologies use in the classroom and student learning outcomes are conflicting, it is undeniable that many students are engaging in intensive distractive multitasking with digital devices in classes. With the rapid growth in device choices, their portability, and availability, this issue warrants immediate attention from educators. The study also demonstrates that a simplistic solution to address the digital distraction problem is neither advisable nor effective. To reduce digital distraction, educators need to tackle the heart instead of the surface of the problem. Therefore, neither an overall ban on devices nor ignoring the problem should be the solution. The study recommends a multi-faceted approach that can potentially not only help reduce digital distraction but leverage information technologies as effective learning and teaching tools. For example, this study found that the levels of Internet addiction among university students are worrisome. In addition, classroom and instructor characteristics figure prominently as to why students are distracted in the classroom. Therefore, online education and massive online open courses (MOOCs) may prove to be more suitable for some students as they offer more flexible, self-paced and active online learning experiences.

Interesting distinctions regarding digital distraction intensity and constructs influencing digital distraction are found across cultures in this study. This implies that country level constructs such as national cultural and technological characteristics cannot be ignored when studying digital distraction across cultures. Understanding these issues also helps us to make educated predictions of issues relevant to digital distraction in cultures where studies have not been

conducted. It is also recommended that future studies focus on the impact of national cultural and technological constructs (e.g. relative importance of various culture values) on digital distraction so that more accurate models across countries can be developed.

There are a number of limitations to this study. First, the self-reported data employed in this study may contribute to over and/or under-estimation. This argument is derived from the rationale that students tend to underreport items related to Internet addiction and in-class digital distraction. We encourage future studies to employ more objective measures such as computer usage and Internet traffic volume to corroborate the findings of this study. Also, an issue may be raised about the nature of Internet addiction. For example, are the student addicted to private Internet use (e.g. surfing the web, social networks, gaming, etc.) or learning-related Internet use (e.g. using e-learning tools, working on assignments from other courses, etc.)? Future studies are recommended to distinguish between these two types of Internet addiction. Second, data from only a few universities in each country were used in this study; therefore, the sample may not generalize to other universities that demonstrate substantial differences in student bodies and/or Internet use policies. Finally, there may be additional factors that further explain students' in-class digital distraction that are not included in this study.

Overall, this research enhances our understanding of the motivations behind students' in-class digital distraction from a cross-cultural perspective. While there is no panacea for student digital distraction, a comprehensive approach that includes heightening student awareness of Internet addiction, effectively integrating technologies in teaching, and developing strategies and policies for effective classroom management would be a good starting point. Simplistic reactions and simply ignoring the problem are neither productive nor realistic in light of the proliferation of hand-held devices and information technologies. Further research that enhances our understanding in this area will help turn information technologies into an instructor's ally as opposed to an adversary. Future studies should focus on evaluating the effectiveness of the strategies recommended by this study in reducing digital distraction behaviors in the classroom. Furthermore, understanding of digital distraction in higher education can perhaps be extended to the corporate context to reduce technology-related dysfunction at work.

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