Factors contributing to technology-enabled distractions in the classroom: a case study of students at the Polytechnic of Namibia

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Abstract

Classroom access to computers and the Internet may be indispensable for teaching and research both for the student and the teacher. Yet, these technologies can also be an impediment to learning as students may engage in actions unrelated to classwork such as texting, web browsing, e-mailing, online gaming, online shopping or a myriad of other activities. This paper examines the extent of this behavior by college students and the factors that may contribute to this behavior. The factors that were studied include the student's addiction to the Internet, learning style, classroom environment, and other individual student factors (gender, age, etc.). Data for this research were gathered using a questionnaire from 213 Polytechnic of Namibia students. The results show that the level of Internet addiction, the degree of mismatch between learning and instructional styles, and some individual factors have significant impact on the degree to which students engage in distractive activities. The paper also discusses the pedagogical and classroom management implications both for educators and administrators.

Keywords: Internet addiction, digital distraction, learning style, technology use in class, technology-enabled teaching

1. Introduction

Numerous studies have emphasized the benefits of laptops, tablets, mobile devices, and the Internet in the classroom (Maki, Maki, Patterson and Whittaker, 2000; Saunders and Klemming, 2003; Wen, Tsai and Chang, 2004). These studies focus on information technologies' abilities to engage students, facilitate faculty-student and student-student interactions, and create active learning opportunities (e.g. Driver, 2002; Fitch, 2004). 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). They assert that the technology is likely to cause cognitive overload and attention distraction in the classroom. Several studies have found that the use of digital technologies (e.g., computers, mobile phones, Internet) in the classroom is negatively associated with course performance and self-reported understanding of course material (Fried, 2008; Junco and Cotton, 2011; Kraushaar and Novak, 2010; Martin, 2011; Wurst, Smarkola and Gaffney. 2008). For example, Martin (2011) reports that holding business statistics classes in a computer equipped classroom had a negative effect on student performance. In addition, research studies by Wood, et al. (2012) found that students not using any digital technologies in the classroom outperformed students with technology use.

There is mounting evidence that students are often using laptops, mobile phones, Internet, and other digital technologies during classroom lectures for activities that are irrelevant to the class. These distractions take the form of playing computer games, texting, e-mailing, checking social networking sites (e.g., Facebook, twitter), surfing the web, or shopping online (Akst, 2010; Burns and Lohenry, 2010; Campbell, 2006; Heffernan, 2010; Rajeshwar, 2010). University lecturers and professors claim that they are finding it increasingly difficult to compete with the colorful and entertaining contents on the Internet. As the result, many universities are reacting to this troubling phenomenon by restricting computer, mobile phone, and Internet access in the classrooms (Melerdiercks, 2005; Adams, 2006). However, simply blocking access to technologies without carefully studying the root causes of technology-led distraction in the classroom seems irresponsible and inconsistent with the push of many educational institutions to embrace information technologies in teaching/research and learning.

There is currently a paucity of studies in this area, and existing studies provide limited explanation of the psychological motivations behind technology-enabled distraction witnessed in the classroom. We believe that a systematic study of this subject is warranted as more and more mobile technologies are being introduced to students and educators. Studies of this nature may reveal underlying psychological and cognitive issues of university students and identify structural problems in classroom management and pedagogical approaches. The findings could help educators rethink and redesign their course content and delivery approaches to better fit the changing classroom environment. Also, this research will help us validate our research model and allow us to make recommendations to university educators and administrators on how to effectively reduce digital distraction in the classroom while amplifying the benefits of technology in teaching, learning, and research.

First, this research study is designed to gauge the extent to which students are distracted in the classroom by vital technologies. Second, the study seeks to identify factors/variables that contribute to this behavior. This study posits that the level of in-class digital distraction of a student is influenced by the extent of student's addiction to the Internet, student's learning style, teaching styles, and other individual (e.g., age, gender, etc.) and contextual factors (e.g., subject matter, peer behavior, not getting caught, etc.). The data for this research is collected at the Polytechnic of Namibia during the Fall semester of 2012.

2. Research Model

The following model that shows the relationships between the relevant variables (factors) is proposed.

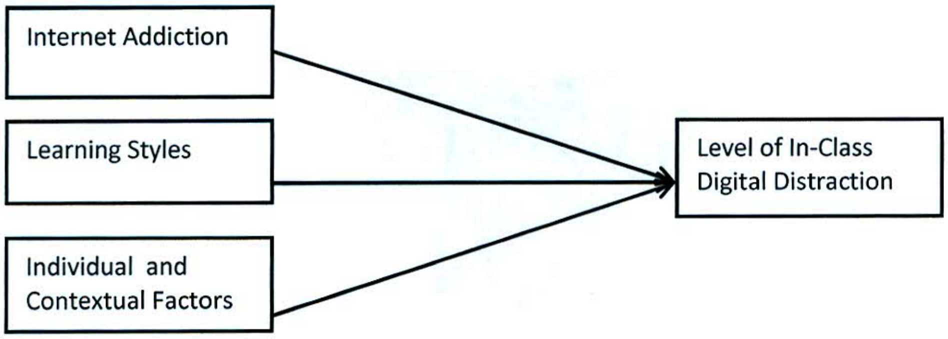


Figure1. Technology-Enabled Distraction Research Model

2.1. Internet Addiction

As society becomes increasingly dependent on information technologies devices, tools, and services, many individuals develop problematic behaviors related to compulsive and excessive technology use. Internet addiction (or Internet dependency) 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. Gencer and Koc (2012) report on a study of Internet abuse among teenagers and Acier and Kern (2011) provide a perspective on problematic Internet use as perceived by addiction counselors. Further, Davis, et al. (2002) found that problematic Internet use went beyond merely spending too much time on the net and that it led to diminished impulse control, loneliness/depression, distraction, and using the Internet as a tool for social comfort. Diminished impulse control is manifested by obsessive cognitions about the Internet and inability to reduce Internet use. Distraction involves using the Internet to procrastinate or avoid stressful events, tasks, or thoughts. 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, we argue that one's Internet addiction level affects the level of digital distraction exhibited in the classroom.

2.2. Learning Styles

Research has confirmed that a learner with a strong preference for a specific learning style would have difficulties if the teaching style did not match his or her preferred learning styles (Felder and Silverman, 1988; Bajraktarevic, et al. 2003). The Felder-Silverman learning styles model suggests that students can be classified into four general learning style categories: sensing or intuitive learners; visual or verbal learners; active or reflective learners; or sequential or global learners. Adams (2006) claims that the majority of today's college students are sensing, visual, active, and global learners, gathering facts from the Internet-connected world, usually through some visual representation while most university instruction assumed intuitive, and passive learning styles in which students are expected to take the sequential knowledge being presented and reflect upon it at a later time. He suggests that this incongruence between students learning and lecturer instruction styles is turning students away from classroom engagement to the lure of digital technologies. Therefore, we propose that the learning styles of the students and the incongruence between learning and instructional styles has an effect on the level of in-class digital distraction.

1.3. Individual and Contextual Factors

It is expected that contextual factors such as the subject taken, fellow student behavior, and engaging lecture, as well as individual factors such as student age, gender, and what year of study the student is in, may act as influencers of digital distraction in the classroom. In theoretical subjects like calculus and physics, it is often difficult to keep student attention unless the professor is very engaging and entertaining or the student is interested in the subject matter. A lack of interest in the subject may result in a higher level of digital distraction. We include these contextual and individual variables in our research.

The specific objectives of this research are:

1. To determine the extent to which digital technology distraction is prevalent among university students in Namibia.
2. To identify factors/variables significantly associated with in-class digital technology distraction.
3. To provide recommendations to educators and administrators to reduce and/or mitigate technology-enabled distractions in the classroom.

3. Research Methodology

3.1. Questionnaire Design

A questionnaire consisting of four sections was designed (it is available from the authors upon request). The research model constructs are measured using multi-item scales. The questionnaire items were generated based on an extensive literature review of how previous research had measured the same constructs. Section I of the questionnaire contained items designed to gauge a student's addiction to the Internet. A 20-item Internet Addiction Test (IAT) developed by Young (1998) was used where each item is measured using a 5-point Likert scale (1 = Never; 5 = Very Frequently). The IAT has been tested for psychometric properties (Davis, Flett, & Besser 2002; Widyanto & McMurran 2004; Widyanto, Griffiths & Brunsden 2011). There are three underlying dimensions of the IAT and they are: emotional/psychological conflict; time management issues; and mood modification.

Section II of the questionnaire contained two parts. Items in part one were crafted to assess the level of in-class digital technology distraction and the items in part two were meant to determine the possible causes for the distractive behavior. It was decided to have a student provide their overall impressions on irrelevant technology use in classes over the past six months as opposed to restricting it to one class. This approach, we felt, would yield global and more holistic perspective on digital disruption as opposed to assessing this behavior in a single class/course. In future studies, it may be worthwhile to focus on just one class if the main purpose of the research is to determine digital technology distraction in one lecturer's class, or in one subject. In part one of this section of the questionnaire, there were six items designed to capture the intensity of irrelevant technology use – five items were for specific digital activities (surfing the web, gaming, checking social networking sites, e-mail, and text messaging) and one item was to assess the extent of overall distractive behavior. Each of the six items was measured using a 5-point Likert scale (1= never; 5 = very frequently). For example, one of the items was: "On average, how often did you read and/or send text messages during a class in the last 6 months?" Part two of this section had eleven (11) items designed to ferret out potential reasons for irrelevant technology use and each of these items was measured on a five-point agreement scale (1 = strongly disagree; 5 = strongly agree). Possible reasons listed varied from dislike for the subject matter and/or the lecturer, lecture is boring, not engaging or challenging, mode of teaching is mainly lecture, and instructor not caring about what students' do in class.

Section III of the questionnaire measured learning styles of students using a 20-item scale developed by Felder and Silverman (1988). This scale was chosen over other learning style scales (e.g., those proposed by Kolb (1984); Honey and Mumford (1982)) because it provides four dimensions along which learning preferences can be assessed as opposed to classifying a learner into a few categories. Many research studies involving learning styles have used Felder and Silverman scale (Carver et al. 1999; Kuljis & Liu 2005). Each of the four dimensions in this scale consists of five items. For each item, there are two choices provided. Based upon the options chosen, a student is assigned a specific preference on each of these dimensions. Descriptions of the four dimensions are summarized as provided in Graf, Viola, Leo and Kinshuk (2007):

Active/Reflective – Active learners work actively with the learning materials, prefer communication with others, and learn through group work. Reflective learners, on the other hand, prefer to work alone, think about and reflect on the learning materials.

Sensing/Intuitive – Sensing learners like to learn facts, use standard approaches in solving problems, have patience with details, and relate the materials to the real world. In contrast, intuitive learners like to learn theories, discover relationships, are more innovative and creative.

Visual/Verbal – Visual learners prefer to learn by seeing things like pictures and diagrams. On the other hand, verbal learners like textual representation in written or spoken form.

Sequential/Global – Sequential learners prefer logical incremental steps in solving problems, tend to have a linear learning approach, and are interested in details. Global learners prefer a holistic process, are interested in overviews, and are able to get the whole picture but have difficulty explaining the specific steps.

The final section of the questionnaire captured data on student demographics (gender, age, year in school, field of study, daily time spent online, ability to multitask, and social networks visited).

Finally, before finalizing the questionnaire, it was pilot tested for understandability, readability, and comprehensiveness. An initial version of the questionnaire was shown to a small number of faculty members and students. Their feedback resulted in modifying/rewording several items in the questionnaire particularly those dealing with the measurement of digital distraction behavior and its causes. Since the scales for Internet addiction and learning styles are well established, they were left unchanged.

3.2. Data Collection

Data for this research was collected at the Polytechnic of Namibia during the Fall 2012 semester. A number of classes across campus were chosen as we wanted to cover a wide spectrum of majors and students. Students were asked to complete the questionnaire in class, they were assured of its confidentiality, and they were told that their responses do not necessarily have to pertain to the class they were attending. This process yielded 225 responses of which 213 questionnaires were useable as in the rest large portions were left blank.

4. Results

4.1. Respondent Profile

Table 1 shows the profile of respondents. The male/female breakdown in the sample was: 54% males and 46% females. Nearly seventy-four percent (74%) of the students were under the age of twenty-five and the overwhelming percent of the respondents were undergraduate students (97%) with first and second year students comprising nearly 65% of the sample; Master's students were only 2.5 % of the total. Further, a majority of the students (67.6%) reported spending, on average, less than an hour online per day. However, about 15% reported spending more than two hours online. Interestingly, over 90% of the respondents reported being "somewhat effective" to "extremely effective" in multitasking (being able to perform multiple tasks simultaneously).

Table 1. Profile of Respondents (n = 213) and Distraction Intensities

		n	%	Mean Distraction Intensity (Y)*
Gender				
	Male	113	54.3%	2.22
	Female	95	45.7	2.20
Age				
	Under 20	56	27.5%	2.32
	20 and under 22	61	29.9	2.42
	22 and under 25	34	16.7	2.44
	25 and under 30	26	12.7	1.87
	Over 30	27	13.2	1.51
School Year				
	First Year	65	32.2%	1.94
	Second Year	67	33.2	2.33
	Third Year	33	16.3	2.48
	Fourth Year	32	15.8	2.29
	Masters	5	2.5	2.24
Average Daily Time Spent online				
	Less than 15 minutes	45	21.7%	2.04
	15 and under 30 minutes	47	22.7	2.00
	30 and under 60 minutes	48	23.2	2.40

1 hour and under 2 hours	17	17.9	2.28
2 hours and under 4 hours	13	8.2	2.38
Over 4 hours	13	6.3	2.45
Multi-Tasking Effectiveness			
Not effective at all	18	8.5%	1.98
Somewhat Effective	67	31.5	2.07
Effective	88	41.3	2.28
Very Effective	31	14.6	2.24
Extremely Effective	9	4.2	2.05

*Distraction intensity is a composite measure with scores varying between 1 and 5.

4.2. Internet Addiction

In order to measure the level of Internet addiction (IA) among students, scores for the three underlying IA dimensions: emotional/psychological conflict; time management issues; and mood modification (Widyanto, Griffiths, and Brunsden, 2011) were calculated. These scores are simply the averages of the items that comprise the given dimension. Further, an aggregate measure of Internet addiction was computed by averaging all twenty IA items. Widyanto, Griffiths and Brunsden (2011) state that average values between 1.00 and 1.95 (corresponds to a 20-item total score of between 20 and 39) signify an *average online user*; values between 2.00 and 3.45 (total score between 40 and 69) indicate an user with *frequent problems with Internet use*; and values between 3.50 and 5.00 (total score between 70 and 100) reflect an user with *significant problems with Internet use*.

Table 2 provides a summary of the Internet addiction among students. Panel 1 of the table reports the overall IA and mean score for each of the three IA dimensions. The overall IA score for all students is 2.36 placing them into "frequent problems with Internet" category. Also, male students have higher mean IA score than female students (2.44 versus 2.28). Mean scores for individual IA dimensions also reveal the same pattern – male student scores are higher than those for female students. However, the t-tests comparing the mean IA scores of males and females showed no statistically significantly differences at the .05 level. However, it is worth noting that for the "time-management problems" and "mood modification" dimensions, the results are significant at the .10 level. Panel two of the table shows the IA results when students were placed into the three IA groups. Note that there are, respectively, 35.3%, 59.3%, and 5.4% of the students in the three categories. Also, a majority (59.3%) of the students fall in the "frequent problem with Internet use" category and a small percent (5.4%) of the students have significant problems with the Internet use. The rest (35.3%) are classified as average online users. More male students are in the "frequent problem" category than female students (66.1% versus 51.1%). On the other hand, the percent of females in the "average online user" category is higher than that of male students (41.3% vs. 30.4%). For the "significant problem" category, such comparisons are not recommended as the sample size is too small ($n = 11$). Finally, to test whether there is a significant relationship between gender and group classification, a Chi-Square test for association was conducted and it revealed a statistically significant association ($\chi^2 = 6.55$; $p = .038$) at the .05 level. Thus, it can be inferred that more male students have problems due to Internet use than female students.

Table 2. Internet Addiction (IA) Among Students

Overall and individual dimension IA Mean Scores

	All (n=204)	Male (n=112)	Female (n=92)	t-value	p
Overall					
IA Score	2.36	2.44	2.28	1.55	0.122
IA Dimensions:					
Psychological/ Emotional Conflicts	2.26	2.30	2.23	0.62	0.533
Time-Management Problems	2.54	2.66	2.42	1.95	0.053
Mood Modification	2.37	2.49	2.24	1.78	0.077

IA Group Percentages

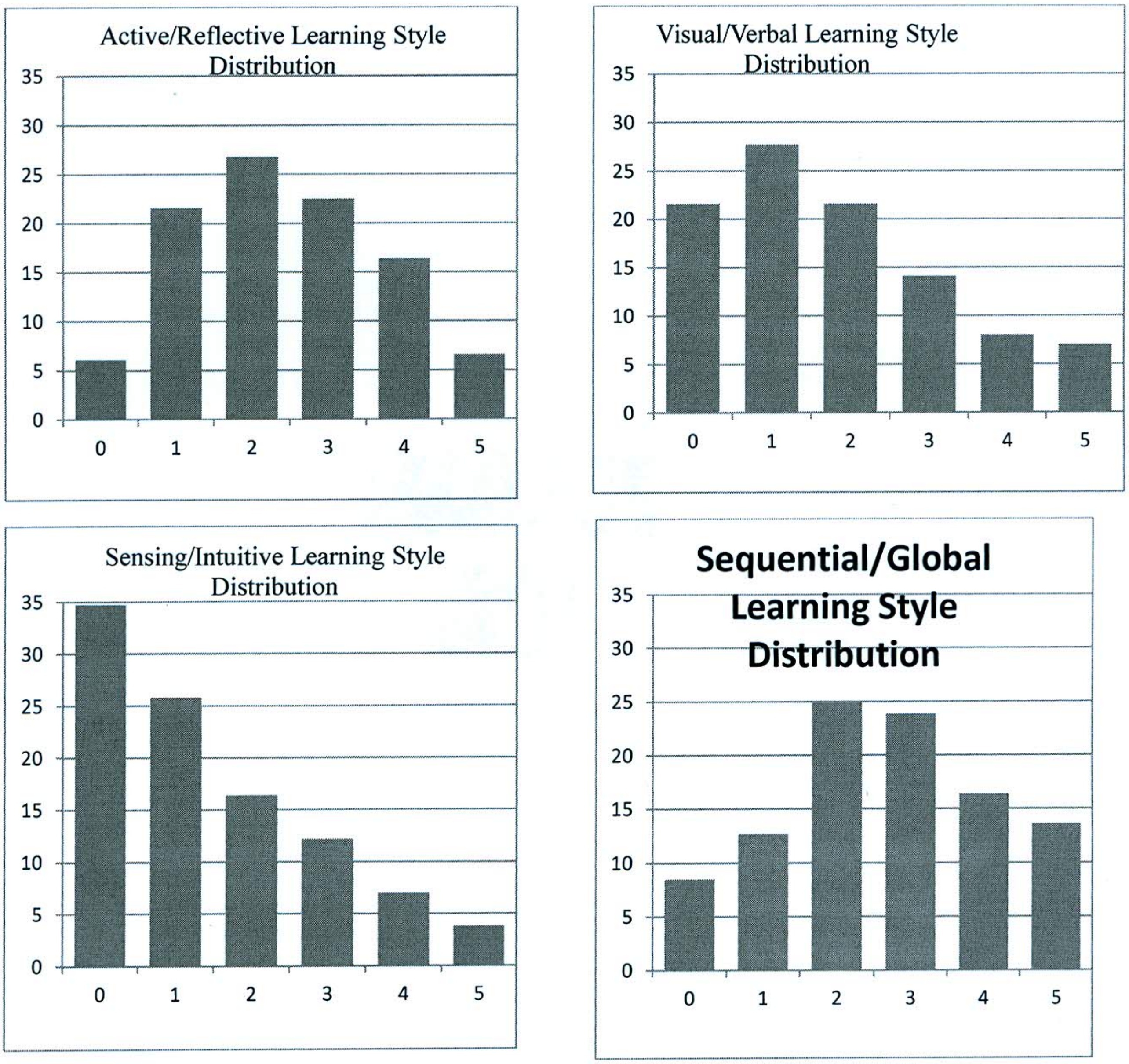
Group	All	Male	Female
Average online user (n=72)	35.3%	30.4%[1]	41.3%
Frequent problems due to Internet use (n=121)	59.3	66.1	51.1
Significant problems due to Internet use (n=11)	5.4	3.6	7.6

[1]Chi-Square test of association between gender and IA group classification is statistically significant (p = .038) at the .05 level.

4.3. Learning Styles

From the 20-item instrument, values for the four learning style dimensions (LSDs) were computed. Each item has two options and the score for a LSD was computed by counting the number of times the second option was chosen among the five items comprising the dimension. For example, in Active/Reflective LSD, if a student selects the second option for each of the five items, it shows a clear preference for "reflective" learning style. On the other hand, if no second options are chosen, then it indicates a preference for "active" learning style. Clearly, the possible values of a LSD are integers between 0 and 5. Distributions of these values for the data are shown graphically in Figure 2. From the four diagrams, it is clear that generally students are visual and sensing learners. On the other two dimensions: active/reflective and sequential/global, there does not appear to be a dominant preference in either *direction.*

Figure 2.Distribution of Learning Styles Dimensions (LSD) of Students (n = 213)



4.4. In-Class Digital Distractive

To gauge the extent of digital distraction occurring in the classroom, students were asked to report how frequently they engaged in activities such as surfing the web, playing computer/mobile games, visiting social networking sites, checking/sending e-mails, and reading/sending text messages. In addition, they were to provide an assessment of the overall distractive digital use in the classroom. A summary of these results is provided in Table 3 which lists these activities according to their frequency. The distractive activity in order of frequency were: reading and sending texts, surfing the web, checking social networking sites, checking and writing e-mails, and playing games on computers/mobile phones.

To ferret out the possible reasons for engaging in such behavior in the classroom, students were asked to rate their agreement/disagreement with a given set of reasons for such behavior. A five-point agreement scale was used (1-strongly disagree; 5=strongly agree). Table 4 shows these results. The top five reasons (top to bottom) for engaging in distractive behavior were:

Computer/mobile phones are allowed to be used in the class
The instructor's lecture is not engaging
The class size is large enough for me to remain anonymous
The instructor does not seem to care
The instructor is not likely to see what I am doing.

It is worth noting that the number one reason for distractive behavior is that technology devices are allowed in the classroom. So, it is a "crime of opportunity" as the technology is right in front of them. The second reason has to do with how engaging the lecture is. Students are more likely to engage in distractive activities if they find the lecture un-engaging and thus not keeping their attention. The third and fifth reasons deal with the large size of the class providing anonymity and the fact that the instructor is not likely to notice them using their digital devices for activities not related to the class. The fourth reason is when the instructor does not care whether or not students are engaging in such distractive activities.

The low ranked reasons are also worth mentioning as it did not matter to students whether the subject was boring or not challenging, dislike for the subject or the lecturer, delivery being primarily lecture, or seeing fellow students engage in distractive activities.

Table 3.Mean and Standard Deviation of Distractive Activities

Activity	Mean (SD) Frequency Score[1]
• Surf the Web	2.31(1.21)
• Play computer/mobile phone games	1.50(1.01)
• Check social networking sites	2.20(1.50)
• Check/write e-mails	1.82(1.20)
• Read/send text messages	3.18(1.49)
• Overall, engage in distractive activities	2.73(1.45)

[1]A 5-point frequency scale is used (1=never; 5 = very frequently); numbers in parentheses are the standard deviations.

Table 4.Mean and Standard Deviation of Reasons for Distractive Computer/Mobile Phone Use

Reasons (ordered by mean score)	Mean (SD) Agreement Score[1]
• Computer/mobile phones are allowed to be used in the class	2.42(1.42)
• The instructor's lecture is not engaging	2.38(1.38)
• The class size is large enough for me to remain anonymous	2.37(1.51)
• The instructor does not seem to care	2.35(1.41)
• The instructor is not likely to see what I am doing	2.25(1.35)
• The subject of the class is not challenging	2.17(1.38)
• The delivery method of the class is primarily lecture	2.17(1.28)
• The subject of the class is boring	2.15(1.36)
• I see other students doing it	1.87(1.27)
• I do not like the subject of the class	1.73(1.13)
• I do not like the instructor	1.60(1.16)

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

4.5. Regression Analysis

To develop a model that identifies variables and their relationships with the level of digital distraction behavior of students, an Ordinary Least Squares (OLS) regression analysis was performed. Explanatory variables considered included Internet addiction, learning styles, certain student demographic variables, and key classroom, course and instructor characteristics. A brief description of the variables considered follows:

Y = Distraction intensity. This variable is computed as the average of the five technology-enabled distractive behavior intensities (surfing the web, playing computer/mobile games, checking social networking sites, using e-mail, and reading/sending texts)
X_1 = Active/Reflective LSD score.
X_2 = Sensing/Intuitive LSD score.
X_3= Visual/Verbal LSD score.
X_4 = Sequential/Global LSD score
X_5 = Internet Addiction (IA) score
X_6 = Gender (0=male; 1=female)
X_7 = 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).
X_8 = School year. This is measured as a categorical variable (1= first year; 2 = 2nd year;
3 = 3rd year; 4 = 4th year; 5 = Masters).
X_9 = 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).
The following five (5) variables are measured on a 5-point Likert scale (1=strongly disagree; 2=disagree; 3=neutral; 4=agree; 5=strongly agree) and these are the five top rated variables identified by the students for digital distraction in the class.(see Table 4):

X_{10} = The instructor is not likely to see what I am doing.

X_{11} = The instructor does not seem to care.
X_{12} = The instructor's lecture is not engaging.
X_{13} = Computers/laptops are allowed to be used in the class.
X_{14} = The class size is large enough for me to remain anonymous

To check for the multicollinearity problem 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, et al. 1988). In this analysis, none of the VIF values exceeded the threshold of 10 and thus, there was no evidence of multicollinearity. Next, the regression analysis was performed using the backward elimination method where initially all variables are introduced in the model and then step-by-step non-significant variables are eliminated – resulting in a simplified regression model. This process yielded a model that only retained six variables: X_4, X_5, X_7, X_8, X_{10}, and X_{12}. Information regarding the regression model - regression coefficients, standard errors, and p-values are shown in Table 5.

Table 5. Regression Analysis Results

Variable	Description	Unstandardized Regression Coeff.	Standardized Regression Coeff.	Standard Error	t	p
Constant		0.560	--	0.245	2.28	.024
X_4	Sequential/Global LS	0.071	0.111	0.036	1.99	.050
X_5	Internet addiction	0.333	0.262	0.074	4.47	.000
X_7	Student age	-0.149	-0.218	0.040	2.92	.000
X_8	School year	0.136	0.171	0.047	2.92	.004
X_{10}	Instructor is not likely to see what I am doing	0.250	0.359	0.056	5.39	.000
X_{12}	Instructor's lecture is not engaging	0.090	0.132	0.045	2.004	.047

Dependent variable: Y = Digital Distraction intensity
Adjusted $R^2 = 0.44$
$F = 24.80$, $p = .000$

The estimated model, overall, is statistically significant ($F = 24.80$; $p = .000$) at the .01 level of significance. Further, the coefficient of determination, adjusted for degrees of freedom, R^2 is equal to 0.44, indicating that 44% of the variation in the dependent variable, student digital distraction intensity, is collectively explained by the six variables.

[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 $VIF_j = \infty$.

Note that in Table 5, student age (X_7), has a negative standardized regression coefficient with a value of -0.218 indicating that older students are less prone to digital distraction as compared to their younger counterparts. This phenomenon is further noticeable when digital distraction scores are compared for the five age groups (see Table 1) using an analysis-of-variance (ANOVA). This analysis indicated statistically significant differences among the five age groups ($F = 6.773$, $p = .000$). Post hoc analysis showed that the oldest two age groups (25 and under 30, and over 30) were statistically similar in distraction intensity but they differed significantly from the youngest three age groups. Thus, the ANOVA results confirm the regression analysis results for age. For the rest of the variables, the signs of the standardized regression coefficients were all positive indicating that they have a positive association with digital distraction intensity. This shows that student with predominately global learning styles, non-engaging instructors, greater Internet addiction, later in college, and with low likelihood of instructor noticing what they are doing in class, exhibit increased levels of digital distraction.

It is also worth noting that the magnitudes of the standardized regression coefficients show that variable X_{10}: instructor is not likely to see what I am doing, has the highest value (0.359) indicating it to be the most important of the variables. This is followed by Internet addiction (0.262), student age (- 0.218), school year (0.171), non-engaging instructor (0.132), and sequential/global learning style (0.111).

5. Summary and Conclusions

The results show that a majority of college students in Namibia have a moderate to severe addiction to the Internet with male students being more prone to IA than female students. Nevertheless, about a third of the students are found to be average online users with no significant problems in the use of the Internet. There are several research studies that have examined the IA among college students (Christakis, et al., 2011; Hamade, 2009; Kittinger, et al., 2012; Zhang, Clinton, and McDowell, 2008). The analysis also reveals that many students are using their mobile phones and computers while in the classroom to engage in distractive activities that have nothing to do with learning. Most commonly reported in-class distractive activity is sending and reading text messages. It is followed by surfing the web, visiting social networking sites, checking e-mails, and playing computer/mobile games. While mobile phones and computers are excellent conduits of information, they are also tools of mass distraction (Maclean's 2010). While a blanket ban on digital devices may not be advisable or may not even be practical, there is an urgent need for developing and implementing policies for the use of digital devices in the classroom. First, an enforceable strict code of conduct for the use of digital devices in the classroom is needed which students need to accept and adhere to. For it to be practical and equitable, it needs to be implemented university-wide, but at the very minimum, at the college/departmental level. Leaving the enforcement of such a policy to an individual instructor is likely not to work as these policies could vary greatly from instructor to instructor depriving students the benefit of an uniform policy to follow. Second approach could be to allow access when needed for classwork, but otherwise block the access by turning off Wi-Fi and jamming mobile signals. This approach may be impractical as it may not be possible to turn off mobile or Wi-Fi access in one classroom without affecting the access in classrooms next to it. The third approach is to identify factors that influence student's propensity to engage in distractive behavior and develop strategies to influence these factors in order to curb classroom digital distraction.

In this paper, through the use of regression analysis, factors are identified that significantly influence the levels of digital distraction among students. Variables that lead to increased digital distraction are: Internet addiction level, years in college, global learning style, inability of the instructor to notice student behavior in class, and un-engaging lectures. Only one variable, age, has a negative association with digital distraction, i.e., the older the student, the less likely he/she is to engage in distractive activities. There are several implications of these results. Un-engaging lectures is one of the variables that contributes to distractive behavior. In this era of rapid advances in information technology, availability of a plethora of handheld devices, and students who are accustomed to multi-tasking and expect to be constantly entertained, it is essential that teaching methods and classroom management account for these realities. Therefore, effective computer-classroom integration that uses these new tools and technologies for effective student learning is called for. Faculty training in this integration can go a long way in keeping students engaged. Concole, Dyke, Oliver, and Seale (2004) have developed a model that purports to support varying teaching approaches of faculty in a technology-rich environment. This training could mitigate the digital distractive tendencies of students. Next, students are more likely to engage in distractive behavior if they believe the instructor is not able to see their actions in class. This could be a result of large class size where it is nearly impossible for the instructor to continuously monitor every student's actions. Or it could be that the instructor simply ignores students' distractive behavior. This clearly means that students will get away with this behavior if they think they can. This is an issue of classroom management and it is incumbent on the instructor to maintain a professional classroom environment in which students' know the code of conduct and refrain from engaging in distractive activities.

The regression analysis also revealed that students with global learning styles are more likely to engage in distractive activities. Recall that global learners have a preference for a "holistic" learning process and they are interested in getting the whole picture in contrast to sequential learners who opt for a linear approach – learning in increments and a preference for details. Given that students in our study are a mix of sequential and global learners (see Figure 1), the teaching approach and course materials need to be developed and organized to cater to the learning styles needs of the diverse students. In the absence of the aforementioned teaching style change, global learners will continue to be distracted by digital technologies.

It is also no surprise that Internet addiction was positively associated with digital distraction. Honestly, educators do not have much control over this phenomenon as advanced tools and technologies are becoming available that allow instant access to a plethora of information and communication capabilities. Students succumb to the temptations of these technologies in the classroom especially when the lecture is not keeping their interest and they do not believe they will get caught in the act. Further, the research showed that the longer a student is in college, the more likely he/she is to engage in distractive behavior. One viable explanation of this could be that over time students have become accustomed to in-class digital distraction – so it is a "learned behavior."

There are several implications of these findings for both educators and administrators. First, a professional code of conduct for students need to be developed that clearly states the expectations with respect to the use of digital technologies for non-class use. This should be similar to plagiarism and ethical behavior policies that are widely disseminated by many universities to students in individual courses as well as during student orientation sessions. Digital distraction policies must also become an integral part of the information provided to the students upon their enrollment at a university and this policy need to be emphasized in each class by the instructors. Second, in view of the fact that students have access to mobile phones, computers, and other tools in the classroom, courses and curriculum should be modified to integrate these technologies into the curriculum to enhance learning. The traditional sage-on-stage model of teaching is not conducive to the technology-course integration. It is incumbent on the administration to provide facilities and technology infrastructure for effective faculty training for such integration to occur. In the absence of a well-planned strategy on the part of the administration, the technology-course integration efforts are likely to be sub-optimal and not propagate throughout the university. Third, instructors themselves must take charge of their classes and not tolerate digital distractive activities. Simply ignoring this behavior is not going to make it go away. In addition, instructors must develop strategies to make their lectures engaging and interactive to keep student interest. Teaching workshops and brainstorming sessions among instructors to share "best practices" could go a long way in delivering inspiring lectures.

There is no panacea for student digital distraction. However, a comprehensive approach that includes heightening student awareness of the distraction issue, integrating technology into courses to improve learning, making courses engaging and interactive, and developing strategies and policies for effective classroom management will a good starting point in curbing this student behavior in the classroom.

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