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Canadian university students in wireless classrooms: What do they do on their laptops and does it really matter?☆

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ABSTRACT

Two studies were conducted to examine what undergraduate students do on their laptops during class time and the extent to which laptop usage behaviors are associated with academic success. In Study 1, a sample of 1129 students from a Canadian university completed a survey measuring prototypical behaviors emitted on laptops during class time. Results of factor analyses indicated that laptop behaviors can be regrouped in two dimensions: School related and school unrelated laptop utilization. School unrelated laptop behaviors were significantly associated with lower levels of self-reported academic achievement and satisfaction. School related laptop behaviors were positively associated with academic satisfaction. These results were invariant across different faculties on campus. In Study 2, another sample of 88 students was recruited to examine the longitudinal association between laptop behaviors and semester grade point average obtained at the end of the semester. Results of Study 2 showed that school unrelated laptop behaviors were prospectively associated with lower semester grade point average, even after controlling for a series of potentially confounding influences (i.e., self-regulation failure, motivational deficit, disorganized learning, internet addiction, and school disenchantment). Overall, these results provide theoretically important support to suggest that in-class laptop utilization is a unique and contemporary mode of learning that should not be treated as an epiphenomenon merely accountable and reducible to other sources of psychological influences.

1. Introduction

The visage of higher education has been revitalized with the recent arrival of wireless networking in the classrooms of Canadian universities. Have you ever noticed that some students are on their laptops as you are trying your best to teach and maintain their interest? Nowadays, a large proportion of undergraduate students are using laptop computers, even in the traditional lecture-oriented classes that do not mandate the use of this technology (Fried, 2008). Did you interpret these behaviors as a sign of limited studentship or did you think it was an appropriate way of connecting with and expanding upon the course material? What were they doing on their laptops, and after all, did it really matter?

The proliferation of wireless networks in the classrooms creates new learning opportunities and educational challenges. Indeed, both professors and students need to manage the growing excitement over Internet applications such as online conversations (*Skype, MSN*), instant news blogging (*Twitter*), social networking (*Facebook*), informal research (*Wikipedia*), audio/video entertainment (with headphones), and multiplayer online gaming. The potential side effect of such craze, however, is the inappropriate usage of laptops by undergraduate students. This is a controversy that has stirred a passionate debate in the popular press. Reporters have documented the preoccupations from students, professors, and parents regarding the risks of inappropriate utilization of laptops during class time (e.g., Day,

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2007; McWilliams, 2005; Pinchin, 2009; Young, 2006). However, knowledge about the benefits and downsides of laptops during class time remains mostly anecdotal and speculative. Thus far, the paucity of research on this issue has often left professors underprepared to adapt their teaching style to the ever increasing number of students equipped with wireless computers in their classrooms. As a result, professors from several institutions have been left with little options but prohibiting students from using laptops in their classrooms (for an extensive review of banning cases, see McCreary, 2009). Banning laptops seems like a premature decision given the rarity of research on this matter in both Canadian and American universities. How laptops are being used during class time in traditional lecture rooms is a timely empirical question given that universities are now welcoming a young generation of multitasking students who were raised using emerging technologies in most areas of their daily lives (Roberts, Henriksen, & Foehr, 2009).

2. Laptop behaviors during class time

A number of universities have adopted a *ubiquitous computing environment* that tries to integrate the wireless laptops within an interactive teaching process (MacKinnon et al., 2006, p. 15). Research on the benefits and challenges of laptops in higher education has generally focused on these integrated learning environments (for complete reviews, see Penuel, 2006; Weaver & Nilson, 2005) which, however, remain the exception rather than the standard practice of computing across North American universities. Therefore, it remains uncertain what is occurring when students are using their wireless laptops in a traditional class not formatted for this emerging technology (Salinas, 2008).

In a recent survey of 137 American undergraduate students, a majority of students (64%) reported using their laptop during classes (Fried, 2008). Overall, students spent an average of 23% of their class time on the laptop doing anything but taking notes. Their multitasking behaviors included checking email (81%), using instant messaging (68%), surfing the Internet (43%), playing computer games (25%), and other activities such as online shopping (35%). Similar results were obtained with a larger sample of 450 law school students from three American universities (McCreary, 2009). Specifically, 71% of students admitted surfing the web during classes. Their behaviors included emailing (87%), instant messaging (38%), and browsing sites unrelated to the course (42%).

The study of McCreary (2009) shed light on some of the factors contributing to such behaviors. Students reported surfing the web when they were bored by the course or uninterested by the questions raised by fellow students. Of particular interest, Fried (2008) explored the potential consequences of these behaviors. Students perceived laptops as more disturbing than common distractions (e.g., conversations among students, noise in the corridors) and fatigue. Further analyses revealed that students who used their laptops more frequently during classes were 1.87 times more likely to obtain lower academic grades, even after controlling for confounders such as scholastic abilities and class attendance. These findings are comparable to those of experimental studies in which students assigned to a condition of laptop utilization obtained lower scores on a subsequent performance test compared to a control group where students had to close their laptops (Hembrooke & Gay, 2003) or take note using the traditional paper-and-pencil (Wood et al., 2012). Similar results were reported in a study in which students were either instructed to exclusively take note on their laptop or to alternate between note taking and off-task behaviors designed to mimic prototypical usage of laptop by students during classes (Sana, Weston, & Cepeda, 2013).

Although informative, these few studies suffered several limitations. First, most correlational studies have described initial prevalence of in-class laptop utilization of university students before the recent outburst of enthusiasm for social networking tools like *Facebook and Twitter*. Second, these studies were conducted with relatively small samples of students and in American universities exclusively. Thus, one can only speculate about generalization to other populations, such as Canadian students. Third, these studies were not consistently conducted in traditional class settings. Research is much needed in traditional lecture-oriented classes where laptops are neither mandatory nor restricted by the professor. Fourth, samples were not representative of students across faculties. For instance, students in fine arts and in chemistry may not use laptops the same way because of specificities inherent to their respective curricula. Finally, and most importantly, these studies did not examine whether the association between laptop utilization and academic success can be confounded by a series of other explicative factors consisting of personal characteristics (e.g., school motivation, personality, Internet addiction) that could predispose students to use their laptop in a leisure-oriented manner during class time.

3. Overview of the present studies

Two studies were conducted to examine a series of interrelated issues on the conceptual and functional underpinnings of six laptop utilization behaviors that could presumably fall under two larger behavioral realms. *School Unrelated Laptop Utilization* represents the in-class behaviors emitted on a laptop computer during which the attention of the student is pulled away from school-related goals. The goal of the current project was not to identify the specific number of behaviors that could presumably fall under this category. Rather, we assumed that four prototypical behaviors would adequately represent this category of laptop utilization: Sending emails, navigating on web sites that are unrelated to school work, visiting social networks, and watching videos/pictures. This type of behaviors needs to be distinguished from *School Related Laptop Utilization*, which represents the in-class learning behaviors supported by a laptop computer as the attention of the student is centered on school-related goals. Taking notes and searching for complementary information on the web were taken as prototypical representations of the school related usage of laptop during class time.

4. Study 1

Study 1 was based on a large cross-sectional sample recruited to explore the conceptual underpinnings of six prototypical laptop utilization behaviors. Close attention was paid to each of the six laptop behaviors before trying to aggregate them into broader dimensions. These item-level analyses were deemed necessary given the paucity of empirical attention that has been allocated to in-class laptop behaviors among university students in Canada. A first goal was to examine meticulously the frequency of laptop behavior – one by one – among undergraduate students during class time. Although anecdotal reports of professors can be informative at times, they can rely on a biased heuristic salience. Therefore, the item-level analyses ensured that laptop behaviors were prevalent and variable enough to deserve empirical scrutiny. A second goal was to examine whether the average frequency of laptop behaviors differed significantly across groups of

Table 1
Study 1: in-class laptop utilization of university students from four faculties.

	1		2		3		4		*F*	Contrast
	Arts		Social		Health		Sciences			
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*		
1. Taking notes on the laptop	4.17	1.74	4.45	1.70	3.91	1.60	3.89	1.61	8.70**	2 > 3, 4
2. Searching complementary information on the web	3.58	1.40	3.73	1.43	3.59	1.42	3.64	1.43	0.74	–
3. Sending emails with the laptop	3.79	1.81	3.95	1.82	3.92	1.85	3.65	1.82	1.53	–
4. Navigate on web sites that are unrelated to school work	3.88	1.69	3.75	1.67	3.77	1.66	3.33	1.71	4.56**	4 < 1, 2, 3
5. Visiting social networking sites	3.79	1.75	3.83	1.79	3.75	1.71	3.26	1.75	5.81**	4 < 1, 2, 3
6. Using laptop to watch videos/pictures	3.38	1.87	3.30	1.93	3.36	1.84	3.02	1.84	1.81	–
7. Read text messages on phones or other electronic devices	4.43	1.65	4.48	1.63	4.54	1.49	4.13	1.78	3.13*	4 < 2, 3
8. Laptop is a source of distraction	3.14	1.51	3.12	1.51	3.19	1.54	2.80	1.47	3.44*	4 < 1, 2, 3

Note. Arts $n = 163$; social sciences $n = 417$; health sciences $n = 316$; sciences $n = 229$.

students attending different faculties on campus to estimate whether the phenomenon displayed some consistency across different academic concentrations. A third and fourth goal was to estimate the bivariate correlation between each of the six laptop behaviors and two indicators of academic success (academic satisfaction and academic performance) while investigating whether these associations are invariant across faculties. Laptop behaviors that belong to the same behavioral realm should possess a sufficient degree of *functional homogeneity* (Skinner, Edge, Altman, & Sherwood, 2003) – meaning that they should correlate similarly to markers of academic adjustment.

A fifth goal was to conduct advanced factor analyses – based on recent advances in Exploratory Structural Equation Modeling (Asparouhov & Muthén, 2009; Marsh, Muthén, et al., 2009) – to adequately investigate the tenability of a bidimensional model that would distinguish between (1) school-related and (2) school unrelated laptop behaviors. A sixth goal was to investigate the measurement invariance of the proposed bidimensional model across groups of students attending four different faculties. These stringent analyses were necessary to establish the generalizability and equivalence of the measurement instrument among most university students. In other words, the analyses enabled to perform an unbiased comparison of the latent scores of school-related and school unrelated laptop behaviors across groups of students in arts, sciences, social sciences, and health science. Finally, this study sought to estimate the unique relationships of school-related and school-unrelated laptop utilization behaviors with both academic satisfaction and academic performance.

5. Method

5.1. Participants

A sample of 1129 full-time undergraduate students (28.9% male) from a public university in Ontario (Canada) participated in this study. Students were eligible to participate only if they self-identified as using a laptop computer during class time at the time of the recruitment period in October 2010. The participants ranged from 16 to 50 years in age ($M = 19.03$, $SD = 3.01$) and they were either in the first (76.6%), junior (16.7%), sophomore (4%), or senior (2.7%) year of undergraduate studies. They were studying in the social sciences (37%), sciences (20.4%), arts (14.5%), and health sciences (28%) faculties. Participants described their ethnic background as European-Canadians (68.4%), Aboriginal (1%), African-Canadians (4%), Latinos (2%), Asians (9%), Middle-Easterners (4%), or others (11.6%). All students provided informed consent and the study was approved by an institutional Research Ethics Board. First-year students were enrolled in a participation pool and they received one point toward their introductory psychology class. Other participants received a 5$ compensation.

5.2. Measures and procedures

5.2.1. Laptop behaviors

A short scale was created to measure prototypical laptop behaviors that are likely to be prevalent among university students. The items were generated after conducting a review of the empirical studies published on laptop behaviors in higher-education classroom. The items were also inspired by a qualitative study conducted with a sample of more than 100 students in which they were asked to report their school-related and school unrelated usage of their laptop during class time.[1] A panel of seven people with substantial experience in psychological research (two professors, one postdoctoral fellow, and four graduate students) evaluated the clarity, readability, and conceptual precision of each potential item. Items were reformulated and improved on the basis of the educated feedback offered by this research panel.

The final items were written in plain language using familiar words (see Table 1). Double-barreled items as well as colloquial, technical, and specialized words were avoided to ensure that items could be understood by an undergraduate student population. The first six items measured behaviors that we considered prototypical of the use that undergraduate students make of their laptop during class. Two items were added to respectively examine the usage of other broadband electronic devices (i.e., phones or other electronic devices) and to evaluate the extent to which students perceived their laptop to be a distraction (Fried, 2008). Participants were asked to evaluate how they are using their laptop computer during a typical class on a scale anchored from 1 to 6 (1 = *never*; 2 = *very rarely*; 3 = *rarely*; 4 = *often*; 5 = *very often*; 6 = *very very often*).

[1] A manuscript is under preparation to present the results of this qualitative study.

Table 2
Study 1: correlation between in-class laptop utilization and indicators of academic success of university students from four faculties.

	Academic satisfaction				Academic achievement			
	1	2	3	4	1	2	3	4
	Arts	Social	Health	Sciences	Arts	Social	Health	Sciences
1. Taking notes on the laptop	.18*	.02	.01	.02	.06	.04	.06	.01
2. Searching complementary information on the web	.06	.02	.10	.02	−.09	−.10*	.09	−.03
3. Sending emails with the laptop	−.12	−.07	−.13*	−.11	−.20*	−24**	−.15**	−.18**
4. Navigate on web sites that are unrelated to school work	−.32**	−.21**	−.20**	−.28**	−.27*	−.30**	−.21**	−.27**
5. Visiting social networking sites	−.18*	−.16**	−.28**	−.25**	−.19*	−.27**	−.21**	−.22**
6. Using laptop to watch videos/pictures	−.17*	−.19**	−.18**	−.24**	−.23**	−.31**	−.19**	−.26**
7. Text messages on phones or other electronic devices	−.24*	−.11*	−.19**	−.27**	−.32**	−.19**	−.18**	−.20**
8. Laptop is a source of distraction	−.25*	−.16**	−.13*	−.22**	−.22**	−.12*	−.27**	−.35**

Note. Arts $n = 163$; social sciences $n = 417$; health sciences $n = 316$; sciences $n = 229$. None of these correlations significantly differed across the four groups using significance tests of difference between two correlations ($Z < 1.96$, $p > .05$).

5.2.2. Educational outcomes

Academic satisfaction was measured using an 8-item subscale from the Multidimensional Students' Life Satisfaction Scale (Huebner, Laughlin, Ash, & Gilman, 1998). Students were asked to rate on a 7-point scale anchored from 1 (*not at all*) to 7 (*totally*) the extent to which each statement refers to their feelings toward university at the present moment. Overall GPA consisted in participants self-reported grades using a scale anchored from 1 (F) to 9 (A+).

5.2.3. Procedures

After providing their electronic informed consent, participants received a link to complete an online questionnaire located on a secured research server (psychdata.com). Participants were instructed to complete the questionnaire at the time of their choice alone in a calm and quiet environment.

6. Results

6.1. Item-level analyses

The first goal of Study 1 was to examine the extent to which students are frequently using laptop behaviors during class time. Although we expected that laptop behaviors would be emitted frequently, we also anticipated much individual differences in laptop utilization among students. As such, the average score of participants fell near the center of our six-point rating scale, with a substantial amount of individual differences as revealed by the large standard deviation (see Table 1).

The second goal was to compare the frequency of these behaviors among students from four different faculties on campus. Results revealed both similarity and differences in the extent to which students from different faculties are emitting the laptop behaviors (see Table 1). Notably, searching complementary information on the web and sending emails with the laptop did not differ significantly across faculties. Students from the science faculty, however, were less likely to use their laptop to take notes, navigate on websites unrelated to school, and visit social networks during class time. The size of these differences was small but non-negligible (Cohen's d from −.25 to −.34).

A third goal of this study was to explore the bivariate association between laptop behaviors and two key indicators of academic success: satisfaction and achievement (see Table 2). Pearson correlations were estimated in each of the four faculties. Fischer test of differences between correlation coefficient revealed that none of the bivariate correlations significantly differed across the four faculties ($ps > .05$). Therefore, correlations can be interpreted directly in the general student population rather than for each faculty, separately.

Results of the bivariate associations indicated that taking notes and searching complementary material were not significantly associated with academic satisfaction and academic achievement. Although sending emails during class was not significantly associated with academic satisfaction, this laptop behavior nonetheless negatively correlated with academic achievement. Navigating on website that were unrelated to school work, social networking, and watching videos/pictures were all significantly associated with less academic satisfaction and less academic performance.

6.2. Bidimensional model of in-class laptop utilization

A fourth goal of this study was to examine the structure of in-class laptop utilization to determine whether a bidimensional model of *school-related* (factor 1) vs. *school unrelated* (factor 2) laptop utilization would provide an acceptable goodness of fit. Given the exploratory nature of this study, we adopted a statistical model that combines the advantages of structural equation models and exploratory factor analyses. More precisely, an Exploratory Structural Equation Model (Asparouhov & Muthén, 2009; Marsh, Muthén, et al., 2009) was tested in which items were set to freely load on two factors. Results of this model provided a good fit (see model 1 in Table 3). Taking notes ($\lambda_{factor1} = .35$, $\lambda_{factor2} = -.12$) and searching complementary information ($\lambda_{factor1} = .73$, $\lambda_{factor2} = -.05$) can be taken as indicators of *school-related laptop* utilization. In contrast, navigating on web site unrelated to school ($\lambda_{factor1} = .13$, $\lambda_{factor2} = .83$), social networking ($\lambda_{factor1} = .12$, $\lambda_{factor2} = .83$), and watching videos/pictures ($\lambda_{factor1} = .24$, $\lambda_{factor2} = .69$) can be taken as indicators of *school unrelated laptop* utilization. Of particular interest, sending email during class time loaded on both factors ($\lambda_{factor1} = .53$, $\lambda_{factor2} = .43$), thus confirming the perhaps obvious multi-functionality of this laptop behavior.

We also tested the fit of this model using a traditional confirmatory factor analysis (Brown, 2006). Omitting the cross-loading would have resulted in a misspecified and under-fitted model (see model 2 in Table 3). As expected, and consistent with the exploratory structural

Table 3
Study 1: results of ESEM, CFA, and multiple group CFA with students from four faculties.

	χ^2	*df*	CFI	TLI	SRMR	Contrast	Δdf	$\Delta\chi^2$	ΔCFI
1. ESEM: two-factor	37.50**	4	.989	.957	.017	–	–	–	–
2. CFA: two-factor	143.29**	8	.938	.883	.043	–	–	–	–
3. CFA: two-factor with cross-loading	50.66**	7	.980	.957	.021	3 vs. 2	1	82.08**	.074
Invariance of model 3 across four faculties									
4. Configural	77.91**	28	.978	.954	.026	–	–	–	–
5. Metric	91.18**	44	.978	.971	.039	5 vs. 4	16	12.32	.000
6. Variance	95.91**	50	.979	.975	.041	6 vs. 5	6	1.70	+.001
7. Uniqueness	101.26**	68	.985	.987	.044	7 vs. 6	18	10.33	+.006
8. Intercepts	149.27**	86	.971	.980	.058	8 vs. 7	18	48.96**	−.014
9. Intercepts – partial[a]	119.99**	82	.983	.987	.052	9 vs. 7	14	18.63	−.002

**$p < .01$. Models 2 to 9 tested with ML robust. Differences in $\chi 2$ are scaled.
[a] The intercepts of taking notes and social networking were freely estimated in social sciences and health sciences, thus meaning that they significantly differ from the intercepts in arts and sciences.

equation model, the addition of the cross-loading resulted in a significantly improved model fit (see model 3 in Table 3). Therefore, a bidimensional model with a cross-loading (i.e., sending email loading on both factors) was retained as the best fitting model.

Furthermore, measurement invariance of this model was tested within the confines of a multiple group confirmatory factor analysis (Vandenberg & Lance, 2000). The results of a first model with no equality constraint across groups (i.e., configural invariance) provided a good fit to the data, thus indicating that the same pattern of fixed and freed parameters can be imposed on the data across groups (see model 4 in Table 3). Adding equality constraints on the loadings (i.e., metric invariance; see model 5 in Table 3), variance (i.e., homogeneity of variance; see model 6 in Table 3), and uniqueness (i.e., error invariance; see model 7 in Table 3) did not produce substantial decrement in model fit. However, adding equality constraints on the intercepts (i.e., scalar/strict invariance; see model 8 in Table 3) resulted in a significant decrease in model fit. Two intercepts (i.e., taking notes, social networking) had to be freely estimated in social sciences and health sciences, thus meaning that they significantly differ from the faculty of arts and that of sciences. After releasing these constraints, the fit of the model did not significantly differ from the model with invariance of the uniqueness (see model 9 in Table 3). Overall, it can be assumed that most parameters in the model were invariant.

Partial scalar invariance is a sufficient condition to enable unbiased estimation and comparison of the latent means across groups (Byrne, Shavelson, & Muthén, 1989; Meredith, 1993). Results indicated that the latent mean of school-related laptop utilization did not differ significantly across the four faculties. However, the latent mean of school unrelated laptop utilization was significantly lower in science compared to arts ($\kappa = -.263$, $SE = .133$, $p < .05$, Cohen's $d = -.23$), social sciences ($\kappa = -.236$, $SE = .109$, $p < .05$, Cohen's $d = -.21$), and health sciences ($\kappa = -.273$, $SE = .115$, $p < .05$, Cohen's $d = -.24$). These small but non-negligible differences indicate that science students are less prone towards school unrelated laptop behaviors during class time.

6.3. Associations of school laptop behaviors with academic success

Two hierarchical multiple regressions examined the relationship of laptop behaviors with academic performance and satisfaction of students, respectively. At step 1, the analysis controlled for students' gender, faculty, and year in the program. Three contrasts variables were created to compare arts students vs. others, sciences students vs. others, and social sciences vs. others. Gender was also contrast coded whereas years into the program was contrast coded to reflect the difference between first-year and other students (see Table 4). All these contrasts were centered. Two-way interactions were included into the model to examine whether the relationship between laptop behaviors and the dependent variable was moderated by the faculty in which students were enrolled. Results are displayed in Table 4. Of foremost importance, the results indicated that school-unrelated laptop behaviors were negatively associated to both academic

Table 4
Study 1: results of multiple regressions to predict indicators of academic success.

	Academic performance				Academic satisfaction			
	ΔF	ΔR^2	β	*t*	ΔF	ΔR^2	β	*t*
Step 1	20.92**	.098			3.30**	.017		
C1: Arts vs. others			−.25	−6.15**			−.14	−3.32**
C2: Science vs. others			.001	.01			−.05	−1.15
C3: Social vs. others			−.23	−6.03**			−.12	−3.02**
C4: Female vs. male			.030	.97			.01	.45
C5: 1st year vs. others			.11	3.74**			−.01	−.11
Step 2	38.18**	.067			35.23**	.068		
School related laptop (SRL)			.08	2.35*			.17	4.98**
School unrelated laptop (SUL)			−.28	−8.50**			−.29	−8.28**
Step 3	.92	.005			.38	.002		
C1 x SRL			−.07	−1.58			.03	.53
C2 x SRL			−.06	−1.35			−.03	−.73
C3 x SRL			−.06	−1.37			−.01	−.29
C1 x SUL			.01	.29			−.02	−.45
C2 x SUL			−.02	−.39			−.01	−.07
C3 x SUL			−.03	−.72			.01	.20

Note. All the β and *t* tests were taken from Step 3. All the betas were standardized. C1–C3: Comparison group coded as 1, other three groups coded as −.333. C4: Female coded as 1, male coded as −1. C5: 1st year coded as 1, other three groups coded as −.333.

performance and satisfaction after accounting for the control variables included at Step 1. School-related laptop behaviors were significantly associated with academic satisfaction but only weakly associated with academic performance. None of the interaction between laptop behaviors and the contrast variables for faculty membership reached significance. Overall, it can be assumed that the relationships between laptop behaviors and each of the two outcomes were similar across faculties.

7. Study 2

The large sample of Study 1 prevented us from accessing the students' dossiers to obtain their objective grade point average. Therefore, the academic performance data may have been influenced by subjective biases in self-report. Furthermore, this study adopted a cross-sectional design that also prevented us from inferring that laptop behaviors are predictors that can prospectively influence the subsequent academic achievement of students. Despite these limitations, we can conclude that academic satisfaction and academic performance are significantly associated with lower usage of school unrelated laptop behaviors during class time.

Study 2 focused on three unaddressed issues in Study 1. The first issue concerns the use of a self-reported measure of academic achievement. In Study 2, we used two objective criteria of academic success. First, we examined the relationship between laptop utilization behaviors and semester grade point average (SGPA). This *absolute criterion* was selected because it is the traditional benchmark used to evaluate the degree of academic success of students during a semester. Second, we examined the extent to which students are performing better than their classmates. This *relative criterion* of academic success is methodologically sound because it takes into consideration the overall difficulty of the courses taken by each student during the semester by creating a discrepancy score between one's individual grade and the average grade of classmates.

The second issue concerns the use of a cross-sectional design in which it was impossible to determine whether laptop utilization behaviors were prospectively associated with future academic performance. In Study 2, laptop behaviors were measured during the semester and both indicators of academic success were obtained at the end of the semester through the official record of the students. Overall, this prospective design and objective data offer a much more rigorous test of the influence of laptop behaviors in predicting real academic performance.

Another pivotal goal of Study 2 was to investigate whether laptop behaviors can predict unique variance in academic performance over and beyond explicative factors that could act as confounders in the relationship between laptop utilization and academic performance. Parsimony may compel one to reinterpret any effect of laptop utilization as an epiphenomenon entirely attributable to more generic sources of psychosocial influences. For instance, if a student spends time of Twitter or Facebook during class, and ultimately scores a poor mark on the final examinations, then the true cause could plausibly be the student's own psychosocial characteristics (e.g., lack of motivation) rather than the laptop behavior per se.

In this study, we considered *five alternative hypotheses* that could potentially explain the association between laptop behaviors and academic success: (1) the self-regulation failure hypothesis, (2) the motivational deficit hypothesis, (3) the internet addiction hypothesis, (4) the disorganized learning hypothesis, and the (5) academic disenchantment hypothesis.

First, school unrelated laptop utilization could easily be portrayed as a *self-regulation failure*. During class time, students must be capable of resisting the temptations or the urge to excessively engage in mental activities that pull the attention away from the course material (Diehl, Semegon, & Schwarzer, 2006). Disconnecting oneself from the gradual learning process unfolding in class – because of more instant gratifications provided by surfing on the internet, social networking, or watching videos/pictures – could certainly be cataloged as a failure to self-regulate. The capacities to self-control (de Ridder, Lensvelt-Mulders, Finkenauer, Stok, & Baumeister, 2012) and to tolerate delays of gratification (Tobin & Graziano, 2010) have been shown to significantly predict academic success. Similarly, procrastination – the likelihood of delaying task investment to the very last minute – has also been shown to be detrimental in the pursuit of academic attainment (Steel, 2007). Despite the potent influence of these self-regulatory factors, the usage of laptop behaviors during class should explain additional and unique variance in academic success.

Second, disengaging from the process of learning with off-task behaviors could obviously be attributable to *a motivational deficit*. Students who lack the motivation to do well in school or to engage wholeheartedly in the process of learning have been shown to be less likely to attain highest levels of academic success (Richardson, Abraham, & Bond, 2012). Lack of instrumental and intrinsic valuing (Hulleman, Durik, Schweigert, & Harackiewicz, 2008) and low levels of perceived school competence (Marsh & Craven, 2006) are other factors that could contribute to academic struggles. Yet, it remains to be determined the extent to which the effect of laptop behaviors are entangled with the motivational deficit of some students.

Third, *internet addiction* remains a controversial phenomenon but the uncontrolled urges to access the internet in some individuals have nonetheless been widely documented in psychological science (Widyanto & Griffiths, 2006). The feelings that internet controls one's behaviors and the obsessive passion towards the internet could easily interfere with the capacity to sustain attention and listen to a professor when the virtual world is only one "click" away. Being impulsively drawn into internet has real-life impacts insofar as it interferes with other important areas of one's life, which of course, might include some difficulties in focusing on important school-related matters (e.g., Kubey, Lavin, & Barrows, 2001).

Fourth, unscholarly usage of the laptop during class time might be part of a broader *disorganized learning style*. Some students adopt a learning style characterized by lateness, absenteeism, and carelessness. It is sometimes difficult for some students to know exactly what, how, and when to study in order to prepare their exams (Elliot, McGregor, & Gable, 1999). Such a propensity toward a disorganized learning style has been associated with difficulties in reaching one's academic goals (Robbins et al., 2004).

Finally, not all students experience positive emotions about their school experience (Pekrun, Goetz, Frenzel, Barchfeld, & Perry, 2011). Emotions such as boredom and anxiety (Pekrun, Goetz, Daniels, Stupnisky, & Perry, 2010) and feelings of emotional and physical exhaustion (e.g., Schaufeli, Martínez, Pinto, Salanova, & Bakker, 2002) are likely to hinder one's capacity to learn and to reach optimal levels of functioning in school work. These feelings of *academic disenchantment* might exacerbate the usage of school unrelated laptop during classes while lowering likelihood of obtaining good academic success.

Laptop behaviors could be seen merely as an indicator of a larger problem of self-regulation failure, motivational deficit, internet addiction, disorganized learning, or academic disenchantment. In contrast, we conceived laptop utilization as a ubiquitous and

Table 5
Study 2: Results of multiple regressions predict end of semester academic success.

	Semester grade point average				Performance relative to classmate			
	ΔF	ΔR^2	β	t	ΔF	ΔR^2	β	t
Model 1: Self-regulation failure hypothesis								
Step 1	2.01	.09			1.77	.08		
Step 2	4.28*	.09			5.17**	.10		
Self-control			.24	1.64			.23	1.50
Gratification			.08	.58			.28	1.23
Procrastination			−.21	−1.70			−.21	−1.64
Attention			−.13	−1.06			−.03	−.28
School related laptop			.06	.43			.07	.50
School unrelated laptop			−.33	−2.26*			−.36	−2.56**
Model 2: Motivational deficit hypothesis								
Step 1	5.98**	.22			7.03**	.25		
Step 2	2.14†	.05			3.70*	.06		
Instrumental value			−.03	−.19			−.03	−.23
Intrinsic value			.04	.30			.02	.20
Engagement			.00	.01			.09	.60
Competence			.46	3.64***			.43	3.44***
School related laptop			.06	.43			.07	.57
School unrelated laptop			−.27	−1.87†			−.30	−2.19*
Model 3: Internet addiction hypothesis								
Step 1	.48	.02			.39	.02		
Step 2	3.50†	.08			4.11*	.09		
Dependence			−.06	−.30			−.01	−.01
Real life impact			−.02	−.16			−.03	−.20
Obsessive			−.07	−.38			−.14	−.82
Conflict			−.09	−.58			−.04	−.29
School related laptop			.14	.85			.14	.89
School unrelated laptop			−.35	−2.32*			−.38	−2.51*
Model 4: Disorganized learning hypothesis								
Step 1	2.42*	.13			2.21†	.12		
Step 2	4.77*	.09			5.16*	.10		
Deep processing strategy			.09	.75			.09	.81
Surface processing strategy			−.02	−.22			.01	.13
Disorganization			−.37	−3.42***			−.35	−3.21***
Late in class			.07	.57			.09	.67
Skipping classes			.10	.72			.05	.36
School related laptop			.14	1.00			.14	.97
School unrelated laptop			−.39	−2.54*			−.40	−2.72**
Model 5: Disenchanted hypothesis								
Step 1	3.83**	.16			4.06**	.17		
Step 2	3.60†	.07			4.60*	.08		
Hope			.17	1.31			.25	2.04*
Anxiety			.10	.81			.11	.84
Bored			−.15	−1.15			−.15	−1.14
Burnout			−.23	−1.56			−.16	−1.11
School related laptop			.15	1.04			.16	1.16
School unrelated laptop			−.33	−2.26*			−.37	−2.65**

Note. †$p < .08$. *$p < .05$. **$p < .01$. ***$p < .001$. All beta and t tests were taken from Step 2. Laptop behaviors were added at Step 2.

contemporary mode of learning that should, in and out of itself, be capable of explaining a significant portion of between-person differences in academic success. Laptop behaviors are part of a popular culture that creates a strong subjective norm on campus. The wireless classrooms have invigorated the learning experience of students by offering unprecedented ways of interacting with the course content. Yet, the uninterrupted connection to internet has significantly increased the pool of potential distracters that could inadvertently compromise the capacity to focus on the heart of the matter. School unrelated laptop behaviors could also hinder the interpersonal process of learning by reorienting the student away from the human – the professor – that is trying to create a learning relationship with them. This continuously accessible blending of resources can either direct the attention toward or pull the attention away from the course material. As such, laptop behaviors during class time create a complex and unprecedented social/educational phenomenon that should, it and out of itself, predict academic success over and beyond other related sources of influence.

8. Method

8.1. Participants

A sample of 88 undergraduate students (27.3% male) from a public university in Ontario (Canada) was recruited to participate in this study. Students were eligible to participate only if they self-identified as using a laptop computer during class time at the time of the recruitment period in March 2011. Also, participants who did not want to authorize the researchers to have access to their grade report at the end of the semester were not recruited for this study (i.e., exclusion criteria). The participants ranged from 17 to 32 years in age ($M = 20.14$, $SD = 2.90$) and they were either in the first (47.7%), junior (20.5%), sophomore (18.2%), or senior (12.5%) year of undergraduate studies. They

were studying in the social sciences (31.8%), sciences (30.7%), arts (5.7%), health sciences (19.3%), and management (11.4%). Participants described themselves as Caucasian (61.4%), African-Canadians (2.4%), Latinos (15.9%), Asians (1.1%), and others (19.3%). All students provided informed consent and the study was approved by an institutional Research Ethics Board. First-year students were enrolled in a participation pool and they received one point toward their introductory psychology class. Other participants received a 5$ compensation.

8.2. Procedures and measures

A few weeks before the end of the winter semester, participants were recruited to complete questionnaires measured their laptop utilization behaviors during class time (see Study 1) and a series of self-regulatory, motivation, internet addiction, learning style, and emotional variables. These 21 variables were measured with psychometrically valid measurement tools described in Appendix.

After providing their electronic informed consent, participants received a link to complete an online secured questionnaire located on psychdata.com. Participants were instructed to complete the questionnaire at the time of their choice alone in a calm and quiet environment. Participants were free to authorize the researchers to access their student record to obtain their winter semester grades.

9. Results

Participants had scattered missing data on some of the 21 variables described in Appendix. Seventy-nine to 88 participants were available for the study depending on the variables to be considered in the analyses. Missing data were treated using multiple imputations (with five imputed datasets) in order to minimize the biases generally associated with listwise or pairwise deletion of participants (Schlomer, Bauman, & Card, 2010). Hierarchical multiple regressions were conducted on each of the five imputed datasets and parameter estimates were pooled using the multiple imputations functions implemented in SPSS version 20. Ten hierarchical multiple regressions were conducted in which a block of control variables was entered in the first step followed by the laptop utilization behaviors in the second step. Five analyses were conducted using the *semester grade point average* and the *performance relative to classmate* as the dependent variable, respectively. For each of these analyses, five distinct models were examined to test whether laptop utilization behaviors can predict incremental variance over and above: (1) self-regulation failure, (2) motivational deficit, (3) the internet addiction, (4) disorganized learning, and (5) academic disenchantment.

Results of these analyses are summarized in Table 5. Overall, school-unrelated laptop behavior was significantly associated with markers of academic success difficulties (i.e., lower semester GPA and lesser performance relative to classmate) even after controlling for markers of self-regulation failure (model 1), motivational deficit (model 2), internet addiction (model 3), disorganized learning (model 4), and academic disenchantment (model 5). Overall, results of Study 2 indicated that school-unrelated laptop behavior can significantly predict subsequent academic performance measured objectively at the end of the semester – even after controlling for the effect of several potentially confounding variables.

10. General discussion

Some laptop behaviors can be categorized as *school unrelated laptop utilization* because they tend to pull the attention of the student away from school-related goals and to result in lower academic satisfaction, semester grade point average, and performance relative to classmate. This type of behaviors needs to be distinguished from *school related laptop utilization*, which represents the in-class learning behaviors emitted on a laptop computer during which the attention of the student is centered on school-related goals. Taking notes and searching for complementary information on the web can be taken as prototypical examples of the school related usage of laptop during class time.

It was found that students from the science faculty were less likely to use their laptop to take notes, navigate on website that are unrelated to school, and visit social networking sites during class time. These results highlight the need to further explore how varying academic demands and teaching style might serve to diminish the usage of school unrelated laptop behaviors during class time. As such, future research should examine how laptop behaviors fluctuate for each student across the various courses in which they are enrolled during a semester. Such an approach would enable researchers to identify key contextual factors that contribute to the laptop behaviors while examining whether their respective effect on subsequent academic success differs according to the type of teaching and the level of difficulty of each particular course.

Results from Study 1 also revealed that the relationship between laptop behaviors and the two indicators of academic success (i.e., academic satisfaction and grades) were invariant across the science, social sciences, health, and arts faculties. This finding provides support for the generalizability and robustness of our findings while indicating that laptop has a unique effect that is not conditional on the context of the student's academic program.

Of particular importance, results of Study 2 indicated that school-unrelated laptop behavior can significantly predict subsequent academic performance measured objectively at the end of the semester – even after controlling for the effect of variables selected to reflect (a) self-regulation failure, (b) motivational deficit, (c) internet addiction, (d) disorganized learning, and (e) academic disenchantment. Higher usage of school-unrelated laptop during the semester was related to lower end of semester grade point average – an absolute indicator of academic performance – and to lower performance relative to other students enrolled in the same courses. These results provide initial and theoretically important support against the alternative hypothesis that laptop utilization behavior is merely an epiphenomenon entirely accountable and reducible to other sources of influences that are already widely studied in the psychological sciences. The laptop behaviors emitted during class time have incremental power to predict the key indicators that are usually taken to benchmark the academic success of university students.

In both studies, school related laptop behaviors were mostly unrelated to academic success of students. At a first glance, this result could be taken as evidence to support the argument that laptops should be closed when students are in university classroom (for an extensive review of banning cases, see McCreary, 2009). However, it is important to highlight the intricate complexities of note taking behaviors (e.g., Kobayashi, 2005). Taking notes on a laptop or on a sheet of paper is rarely sufficient to guarantee that notes are clear, complete, accurate, and properly organized. The quality of note taking behaviors could also be compromised when students with a "bad sense of time" decide to take their emails, chat with a friend, or visit their favorite social networking site without taking into consideration the importance of the

information being presented by a professor. Note takers can also become distracted by the school unrelated laptop behaviors of their fellow students in ways that could diminish their own likelihood of obtaining good grades (Sana et al., 2013). Although school-related laptop behaviors do not seem to help, future research is needed to unpack their effects by identifying for whom and under which circumstances they might exert their expected positive effect on academic success. Latent class analyses (Marsh, Ludtke, Trautwein, & Morin, 2009) would be useful to identify subgroups of students more at risks of seeing their academic success compromised because of *their specific ways* of combining utilization of school related and school unrelated laptop behaviors.

11. Limitations and future directions

In our two studies, we measured six laptop behaviors that are prototypical of school related laptop and school unrelated laptop utilization. Future qualitative research could try to create a comprehensive nomenclature of all behaviors frequently emitted by university students on their laptop during class time. However, technologies and social networking trends evolve at an incredibly rapid pace on the web 2.0 environment. New internet trends and behaviors are regularly appearing on the internet. "Old behaviors" can be rapidly abandoned to the extent that they might become virtually unknown to upcoming cohorts of university students. As such, effort to create measurement instruments based on a comprehensive repertory of specific laptop utilization behaviors seems unwarranted. Prototypical examples of laptop utilization – representing broader realms of behaviors – are less prone to become completely obsolete, thus making our measurement approach more immune to sudden shifts in technological trends on the web.

In recent years, the ever improving broadband technologies have brought a social revolution in the ways people interact and share information with one another (Bui, Myerson, & Hale, 2012). Intelligent phones and tablets have rapidly grown in popularity among undergraduate students. Cellular phones, which used to permit telephone conversations and minimal texting, can now be used as small-scale personal computers to emit most of the laptop usage behaviors that we described in our two studies. We had not anticipated the "smartphone revolution" among university students and professors in the initial planning of our research program on laptops in 2009 – already many technological years ago. Future research should examine whether students can actually emit the school-related behaviors to the same extent and with the same quality on smart phones, tablets, and laptop computers. More research is also needed to directly compare the quantity and types of school unrelated behaviors emitted inside vs. outside of classes (Junco & Cotten, 2012; Rosen, Mark Carrier, & Cheever, 2013) and when students are engaged in different types of schoolwork (e.g., reading, writing, preparing exams).

Laptop utilization behaviors were assessed using a self-reported method. Future research could use sophisticated but more expensive methods in order to observe the types of behaviors emitted by university students. For example, the laptop of consenting research participants could be equipped with software that would track the internet-based activity and emailing frequency of students during class time (Kraushaar & Novak, 2010). Alternatively, participants could wear portable eye-tracking systems that would unable researchers to obtain real-time information on the type of stimuli on which students orient their visual attention during class time. Reports from a peer or a friend could also be used as a low cost alternative to obtain complementary information on the type of laptop behaviors used by a university student during class time.

12. Conclusion

This study provided information that could be useful for university professors, administrators, and service providers on campus. First, students are using both school related and school unrelated laptop behaviors during class time, thus contradicting an impression that laptops should be entirely prohibited in the classrooms. Second, the laptop utilization behaviors do seem to matter because they are significantly associated with key indicators of academic success of university students. Third, the potential influence of laptop behaviors cannot be treated or reduced as an epiphenomenon entirely attributable to other known sources of psychological influences. As a result, laptop utilization behaviors should be considered as an important target that should be part of psycho-educational prevention programs on our campuses. Students should be informed about and learn the socially, educationally, and ethically appropriate ways of using their laptops, tablets, and smart phones during class time. Professors need to be informed about both the potential benefits and challenges resulting from the proliferation of wireless classrooms in higher education. Administrators need to support professors by creating training programs and pedagogical services that could help interested professors to adopt teaching behaviors that would match the ever growing usage of technological devices in our classrooms. In summary, this study contributed to a pressing need for a novel line of psychosocial research that will examine how universities can prepare themselves for the upcoming generation of multitasking students who were raised using emerging technologies in most areas of their daily lives (Roberts et al., 2009).

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Appendix

Constructs	Measure	Example
Self-control	Tangney, Baumeister, and Boone (2004), 13 items, 1–5 scale, $\alpha = .79$, $M = 3.23$, $SD = .64$.	People would say that I have iron self-discipline.
Delay of gratification	Steel (2010), 11 items, 1–5 scale, $\alpha = .93$, $M = 2.62$, $SD = .87$.	My actions and words satisfy my short-term pleasures rather than my long-term goals

(*continued on next page*)

(*continued*)

Constructs	Measure	Example
Procrastination	Steel (2010) 9 items, 1–5 scale, $\alpha = .77$, $M = 3.08$, $SD = .64$.	I delay tasks beyond what is reasonable
Attention regulation	Diehl et al. (2006), 10 items, 1–7 scale, $\alpha = .74$, $M = 4.11$, $SD = .77$.	I can control my thoughts from distracting me from the task at hand.
Instrumental value	Hulleman et al. (2008), 4 items, 1–7 scale, $\alpha = .94$, $M = 4.54$, $SD = 1.21$.	What I am learning in this class is relevant to my life
Intrinsic value	Hulleman et al. (2008), 4 items, 1–7 scale, $\alpha = .84$, $M = 4.18$, $SD = .92$.	Lectures in this class are entertaining
Engagement	Schaufeli et al (2002), 14 items, 1–7 scale, $\alpha = .84$, $M = 3.96$, $SD = .99$.	I can continue for a very long time when I am studying.
Competence	Deci and Ryan (2000), 4 items, 1–7 scale, $\alpha = .96$, $M = 4.38$, $SD = 1.43$.	I feel like I am a competent student.
Internet dependence	Gnisci, Perugini, Pedone, and Di Conza (2011), 24 items, 1–5 scale, $\alpha = .92$, $M = 2.33$, $SD = .72$.	I go online even if I have more important things to do
Real life impact	Gnisci et al. (2011), 15 items, 1–5 scale, $\alpha = .68$, $M = 3.09$, $SD = .56$.	My friends or relatives do not complain because I spend too much time online
Obsessive passion	Séguin-Levesque, Laliberté, Pelletier, Blanchard, and Vallerand (2003), 4 items, 1–7 scale, $\alpha = .86$, $M = 2.70$, $SD = 1.43$.	Because I almost have an obsessive feeling for this activity
Conflict	Markel and Frone (1998), 4 items, 1–5 scale, $\alpha = .90$, $M = 2.69$, $SD = .99$.	Because of the internet, I go to school tired.
Deep processing	Elliot et al. (1999), 5 items, 1–7 scale, $\alpha = .68$, $M = 3.89$, $SD = .98$.	I treat the course material as a starting point and try to develop my own ideas about it.
Surface processing	Elliot et al. (1999), 5 items, 1–7 scale, $\alpha = .89$, $M = 4.82$, $SD = 1.20$.	I study for my courses by memorizing the definitions and concepts.
Disorganization	Elliot et al. (1999), 5 items, 1–7 scale, $\alpha = .94$, $M = 3.29$, $SD = 1.54$.	I often find that I don't know what to study or where to start.
Late in class	Legault, Green-Demers, and Pelletier (2006), 1 item, 1–7 scale, $\alpha =$ NA, $M = 2.74$, $SD = 1.41$.	How often have you been late in class?
Skipping class	Legault et al. (2006), 1 item, 1–7 scale, $\alpha =$ NA, $M = 3.01$, $SD = 1.40$.	How often have you been skipping class?
Academic hope	Pekrun et al. (2011), 6 items, 1–7 scale, $\alpha = .84$, $M = 3.91$, $SD = 1.02$.	I have an optimistic view toward studying.
Academic anxiety	Pekrun et al. (2011), 6 items, 1–7 scale, $\alpha = .87$, $M = 3.96$, $SD = 1.36$.	When studying for my courses, my heart beats fast because I am nervous.
Academic boredom	Pekrun et al. (2011), 6 items, 1–7 scale, $\alpha = .84$, $M = 3.83$, $SD = 1.19$.	The content is so boring that I often find myself daydreaming.
Academic burnout	Schaufeli et al (2002), 15 items, 1–7 scale, $\alpha = .93$, $M = 3.84$, $SD = 1.17$.	I feel emotionally drained by my studies.

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