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Logged In and Zoned Out: How Laptop Internet Use Relates to Classroom Learning

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Abstract

Laptop computers are widely prevalent in university classrooms. Although laptops are a valuable tool, they offer access to a distracting temptation: the Internet. In the study reported here, we assessed the relationship between classroom performance and actual Internet usage for academic and nonacademic purposes. Students who were enrolled in an introductory psychology course logged into a proxy server that monitored their online activity during class. Past research relied on self-report, but the current methodology objectively measured time, frequency, and browsing history of participants' Internet usage. In addition, we assessed whether intelligence, motivation, and interest in course material could account for the relationship between Internet use and performance. Our results showed that nonacademic Internet use was common among students who brought laptops to class and was inversely related to class performance. This relationship was upheld after we accounted for motivation, interest, and intelligence. Class-related Internet use was not associated with a benefit to classroom performance.

Keywords
Internet, laptop, academic performance

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Inside lecture halls at many universities, laptop computers are increasingly prevalent. Many universities now require or recommend that students bring laptops to class (e.g., Michigan State University, 2015), and instructors often post lecture slides online so that students can refer to them during class (Babb & Ross, 2009). Although laptops may be helpful for taking notes (but see Mueller & Oppenheimer, 2014) or promoting class participation (Samson, 2010), they are also a potential source of distraction. In particular, laptops provide easy access to the Internet, and they allow students the appearance of pursuing academic goals, which is not the case when smartphones are used. In essence, laptops might increase the likelihood of self-interruptions, which are more disruptive to the primary task than external interruptions (Mark, Gonzalez, & Harris, 2005). Furthermore, several studies have shown that using portable devices for nonacademic purposes in the classroom is related to diminished learning (Junco, 2012; Kraushaar & Novak, 2010; Risko, Buchanan, Medimorec, & Kingstone, 2013; Rosen, Lim, Carrier, & Cheever, 2011; Sana, Weston, & Cepeda, 2013; Wood et al., 2012) and that this holds true regardless of intellectual ability (Fried, 2008; Jacobsen & Forste, 2011; Ravizza, Hambrick, & Fenn, 2014).

Despite the intuitive and established link between nonacademic portable device use and poor classroom performance, students downplay this relationship and report little or no effect of their portable device use on learning class material (Kirschner & Karpinski, 2010). For example, 62% of students see no problem with texting in class as long as they do not disturb other students (Tindell & Bohlander, 2012). Moreover, another study found that almost half the students believed that texting did not

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influence their grades when, in fact, the amount of texting and their grades were related (Clayson & Haley, 2013). The current study seeks to explain this disconnect between students' perceptions and the actual relationship of their portable device use to classroom learning—specifically, how laptop Internet use relates to classroom performance.

One possible reason for this disconnect is that students have better insight into what is causing them to browse the Internet and are attributing their performance to this explanation. For example, interest in the class or motivation to do well might drive both classroom performance and Internet use. Indeed, 48% of students reported that they texted during class because they were bored (Clayson & Haley, 2013), and Facebook use and Internet surfing increased when ongoing tasks were rated as boring (Mark, Iqbal, Czerwinski, & Johns, 2014). If so, students are rightly attributing their poor performance to the underlying cause (e.g., boredom) rather than to their Internet use per se. We test this hypothesis by assessing whether motivation and interest can account for the relationship between Internet use and classroom performance.

Another possible reason for this disconnect is the use of subjective reports about Internet use. In all but a few studies (Grace-Martin & Gay, 2001; Kraushaar & Novak, 2010), Internet use has been measured by self-report. The use of self-report is problematic for two reasons. First, self-report of this type of data has been found to underestimate actual use (Kraushaar & Novak, 2010). Second, self-report measures may also be susceptible to demand characteristics of the experiment. Although students have an explicit belief that their Internet use has little or no effect on their learning, they may derive an implicit expectation from the questions asked during the experiment; specifically, if they are doing poorly in class, then they must have been distracted by their laptop. Accordingly, to conform to the experimental demand, those doing poorly in the class may report more laptop use than those doing well. If this has been the case with past research relying on self-report, then it is possible that the previously identified relationship between Internet use and classroom performance does not actually exist. Instead, students are reporting Internet use on the basis of classroom performance.

In the present experiment, we directly monitored the frequency and duration of students' laptop Internet use without relying on self-report. To this end, we assessed the relationship between classroom performance and actual laptop Internet use in students in an introductory psychology class. Some of the students agreed to log into a proxy server during class throughout the semester. We also acquired information about their motivation and interest in the class as well as a measure of their intelligence. By tracking actual use rather than self-reported use, we were able to overcome the disadvantages associated with self-report data. Moreover, we have gained some insight into why students believe their laptop Internet use has little effect on their learning of class material, and we were able to determine the kinds of Internet sites that have the most disruptive effects.

Method

Participants

Five hundred seven students enrolled in an introductory psychology class in fall 2014 were invited to participate in this experiment for course credit. One hundred twenty-seven students consented to participate. The final sample consisted of the 84 participants who checked into the proxy server during more than half of the 15 sessions and logged in an average of 12.7 times. Participants who logged in for less than half of the sessions were excluded from analysis.

The majority of participants were freshmen (56.5%) and sophomores (33.9%); there were a few juniors (5.7%) and seniors (4.0%). These percentages were similar to the percentages across the entire class of 507 students (47.1%, 34.8%, 12.7%, and 5.4%, respectively), although more freshmen and fewer juniors participated. Participants did slightly better on the final exam (M = 81.4%, SD = 10.54) compared with the class average of 78.3% (SD = 11.7). This most likely reflects the better attendance of participants, given that they were required to attend class to participate in the study. In fact, participants attended more lectures (83.8%) than the class average (80.3%).

Permission to monitor the browsing activity of participants via a proxy server was obtained from Michigan State University's institutional review board. Students were fully informed that the proxy server would track their Internet activity when connected, and they were guaranteed that this information would remain anonymous and confidential. When asked how their Internet use in this class differed from that in other classes, the average response was 3.3 on a 5-point scale (1 = *I used the Internet much less in this class*, 3 = *About the same as other classes*, 5 = *I used the Internet much more in this class*). Moreover, many students forgot to log out of the proxy server at the end of class, indicating that they were not overly concerned about their Internet use being monitored. Any data inadvertently collected outside class hours were promptly discarded.

Procedure

To record actual Internet use in the classroom, we asked the participants to bring their laptops to class and to connect to the Internet only via the proxy server. The students were shown how to connect to and disconnect from the proxy server, and instructions were also provided online for reference. The participants were asked to log into the server every class period and to use their laptops as they normally would. Data was collected via the proxy server over 15 lectures. Each lecture lasted 1 hr and 50 min with a 10-min break in the middle. Data collected during the break was removed from analysis. The participants received course credit for partaking in the experiment; the amount of credit granted depended on the number of lectures for which they logged into the proxy server. Internet use was not required to obtain credit; the participants could participate in the experiment and receive credit without using the Internet during class. To do so, they simply had to log into the proxy server and then stop usage. Credits were granted to anyone who logged into the server immediately before, during, or after class or during the break. The participants could therefore receive credit without ever disrupting their learning. Any use of the Internet beyond signing into the proxy was voluntary and did not result in additional credits.

Each participant was given a unique username and password to log into the server, which allowed us to differentiate activity among the individual participants. It also allowed us to compare a specific individual's activity with his or her academic performance.

At the end of the semester—after all 15 lectures—an invitation to a survey was e-mailed to each participant. The participants logged in with the same username and password, and they were asked to self-report their Internet use for an average lecture in the same introductory psychology class. They were also asked to rate their motivation to do well in the class, their overall interest in the class, and a number of other variables (for the full survey, see the Supplemental Material available online).

Measures

Actual Internet use. The proxy server logged all HTTP requests (i.e., communications from the computer to the Internet) made by participants, effectively telling us when and where they went online.[1] Most important, the log told us the URLs (i.e., the Web addresses) of the Web sites visited and the time at which each connection was initiated, both of which were tied to individual usernames. We used this information to calculate the following variables of interest.

Average duration online. This measure is an *estimate* of the average number of minutes a participant spent browsing the Internet during each lecture. An HTTP request is not a continuous connection—the Web browser downloads data only as needed. When a new request is made, a new page or item is loaded, but if the contents of a page are already loaded, requests will not be continually made. Therefore, some degree of assumption must be made to get a measure of the time the subject spent viewing the downloaded content. We assumed that requests made within 5 min of each other indicated continuous usage. For most users, multiple requests were made every minute when online. We chose 5 min to better accommodate the viewing of any static content (e.g., reading e-mails, news and sports articles) that is downloaded only once. Nonetheless, when we reran analyses with a stricter interrequest time of 2 min, similar usage averages were obtained.

For example, if a subject's log indicated activity at 10:15, 10:17, 10:18, and 10:20, we interpreted this as one session lasting 5 min from 10:15 to 10:20 because the time between requests was less than 5 min. However, if the log indicated activity at 10:00, 10:02, 10:03, 10:05, 10:20, 10:21, 10:23, 10:25, 10:26, and 10:30, then we interpreted this as two sessions, the first lasting 5 min (10:00–10:05) and the second lasting 10 min (10:20–10:30). Note that this is a conservative estimate because we are not padding the duration by any time after the last request, and it is possible that the individual could have been reading information for the 15 min between the defined sessions (i.e., from 10:05 to 10:20 in the second example).

For each participant, the duration of each session was summed over the 15 lectures, giving us the total estimated time that the participants spent online during the semester. We then divided this sum by the total number of times that a participant logged into the proxy server. This gave us the individual's estimated average duration online during a typical lecture when a laptop was brought to class.

Average number of requests. This measure is the *actual* average number of HTTP requests a participant made during each lecture. Individuals more focused on their Web browsing (than on the lecture) may also be loading more sites and more frequently jumping from Web page to Web page (i.e., accumulating HTTP requests). The higher the number of requests, the more active the Internet user. We therefore tallied the number of requests each participant made during the 15 lectures, and we divided that sum by the number of times that he or she logged into to the proxy server. This gave us the average number of requests made during a typical lecture when the participant brought a laptop to class.

Within both of these variables, we also categorized the data on the basis of the content of the Web site visited. Each Web site was placed into one of seven categories using an online URL categorization system developed by McAfee (https://www.trustedsource.org/): social media (e.g., Facebook, Twitter), e-mail (e.g., Gmail, Hotmail), chat (e.g., iMessage), online shopping (e.g., Amazon, eBay), news and sports (e.g., CNN, ESPN), video (e.g., YouTube, Netflix), and online games (e.g., Sporcle.com, flash games). Therefore, we collected not only the average number of minutes online per lecture but also the average number of minutes spent on social media or online shopping, and so forth. The same categorizations were made for the number of requests as well.

Note that these measures do not reflect the duration or frequency of an individual URL but are within-category measures. For example, duration of shopping would include a jump from one e-tailer to another (e.g., from Amazon to Zappos). Visits to the Desire2Learn (D2L) Web site were considered academic Internet use, given that class-related materials such as the syllabus, lecture slides, and study guides were accessible to students on this site. We also included Wikipedia visits that were related to class material (e.g., "Little Albert") and dictionary sites (e.g., merriam-webster.com) as types of academic use. Wikipedia visits that were not related to class material (e.g., "Longest NCAA Division 1 Football winning streak") were not considered academic use. Translation Web sites were also not included as academic use because the content of what was being translated was not apparent from the URL. Moreover, several students reported doing Spanish homework in class. We also did not analyze any Internet activity occurring outside of class hours or during the break.

Self-reported Internet use. We asked participants to self-report their use (in addition to the actual use recorded by the proxy server) by means of a survey administered after the 15 lectures were completed. The survey asked the participants to estimate their minutes of use for each of our non-classroom-related Web-site categories (e.g., "During a typical class, how much time on average did you spend using your laptop to check social media?"). The survey asked them to make the same estimations for their smartphone use—note that the proxy server monitored only laptop use; connections to the Internet via their smartphones were not monitored. The survey also asked participants how many times they initiated activity in each of the categories, on their laptops and on their smartphones separately (e.g., "During a typical class, how many times on average did you initiate online shopping on your smartphone/tablet?"). Last, the survey asked the participants to rate how interested they were in the class, how motivated they were to do well in the class, and other questions about studying habits (see Supplemental Material).

Classroom performance. To determine whether Internet use was related to academic performance, we used the cumulative final-exam score.

Intelligence. After obtaining permission from the participants, we obtained their composite ACT scores from the university registrar. Composite ACT scores correlate very highly with independent measures of general intelligence (Koenig, Frey, & Detterman, 2008). These data were unavailable for 14 participants, either because they had taken the SAT or because they were international students. Participants with missing ACT scores tended to perform more poorly than others on the final exam, $t(82) = 1.98$, $p = .051$. This may have been due to the lower language proficiency of international students. The groups did not differ from each other on motivation, interest, academic Internet use, or nonacademic Internet use.

Results

Participants spent a median of 37 min per class browsing the Internet for non-class-related purposes with their laptops. They spent the most time using social media, followed by reading e-mail,[2] shopping, watching videos, chatting, reading news, and playing games (Table 1). Social media sites also had the highest number of HTTP requests, but thereafter the order differed: shopping, watching videos, reading e-mail, chatting, reading news, and playing games. Note that the minutes and requests do not add up to the total Internet time. The remaining time and requests reflect Internet use that did not fall into one of the seven categories. These URLs were related to checking background certificates for a Web site; Google-provided services such as calendar, maps, and analytics; visits to university sites (e.g., the registrar); and advertisements. Students also browsed the class-related Web sites for 4 min and approximately 5 requests per class session.

Laptop Internet use and classroom learning

To most accurately assess laptop Internet use, we combined our two initial measures—minutes spent online and number of requests made—to create a primary variable of interest that reflected both aspects of use for each category of Internet use, both academic and nonacademic. This was done by multiplying the two initial measures together in a manner similar to that used by other studies in which both frequency and duration are thought to contribute to the variable of interest (Hume, Van Der Horst, Brug, Salmon, & Oenema, 2010; Meinz & Hambrick, 2010). Our new combined variable for total use was strongly positively correlated with both time online and number of requests—time spent online engaged in academic activities, $r(82) = .92$, $p < .001$; time spent online engaged in nonacademic activities, $r(82) = .51$, $p < .001$; number of HTTP requests

Table 1. Medians and Quartiles for Key Variables

Variable and statistic	Total academic Internet use	Nonacademic Internet use: Using social media	Shopping	Reading e-mail	Chatting	Reading news and sports	Watching video	Playing games	Total
Actual minutes online									
Q_1	0.43	1.30	0.25	0.26	0	0	0.24	0	17.04
Median	3.79	6.30	1.18	1.85	1.03	0.29	1.15	0	36.90
Q_3	11.03	17.54	3.23	6.36	12.14	1.18	3.02	0	56.70
Number of HTTP requests									
Q_1	1.31	6.86	1.00	1.02	0	0	0.34	0	174.00
Median	4.73	38.43	17.89	3.58	1.65	1.19	4.09	0	538.55
Q_3	12.26	142.74	98.00	11.28	13.95	12.87	19.91	0	879.64
Self-reported minutes online									
Q_1	—	5	0	5	—	0	0	0	—
Median	—	15	3	10	—	1	0	0	—
Q_3	—	30	10	15	—	5	1	0	—

Note: Q_1 = first quartile, Q_3 = third quartile.

for academic activities, $r(82) = .83$, $p < .001$; number of HTTP requests for nonacademic activities, $r(82) = .95$, $p < .001$. Given that our data were positively skewed, we used a square-root transformation (Howell, 2007) to normalize Internet use so that skewness was below 2 (i.e., skewness = 1.58; Hancock & Mueller, 2010).

Nonacademic Internet use, composite ACT scores, motivation to do well, and interest in the class were all significant predictors of the score on the cumulative final exam (Table 2). Academic Internet use was not related to final-exam score, $r(82) = .09$, $p = .43$. Neither ACT scores nor motivation was significantly related to laptop Internet use for class-related or non-class-related purposes. Interest in the class approached significance, $r(76) = -.19$, $p = .096$; that is, there was a trend for greater interest in the class to be related to lower laptop Internet use for nonacademic purposes. Motivation and interest were also related such that greater interest in the class material predicted higher motivation to do well. None of the other correlations were significantly different from zero.

A hierarchical multiple linear regression analysis was used to evaluate the relationship between nonacademic Internet use and final-exam score while accounting for intellectual ability, motivation, and interest. Full data for 61 participants was entered into the model. The hierarchical regression revealed that at Step 1, motivation, interest, and ACT score contributed significantly to the regression model, $F(3, 58) = 5.05$, $p < .005$, and accounted for 20.7% of the variation in the final-exam score. Introducing total Internet use to the regression model at Step 2 explained an additional 5.6% of the variation in the final-exam score, and this change in R^2 was significant, $F(1, 57) = 4.36$, $p < .05$. Although lower interest in the class was related to higher Internet use on laptops, lack of interest did not completely account for the relationship between Internet use and exam score. Thus, the disconnect between students' beliefs about and the actual relationship between classroom learning and exam score is not explained by students' attributing their Internet use to low motivation or interest in the class.

Moreover, we replicated the finding that intellectual ability was not related to Internet use for nonacademic purposes, and Internet use predicted exam score even when we accounted for ACT scores. To examine these

Table 2. Correlations Among Cumulative Final-Exam Score, Actual Internet Use, Composite ACT Score, Motivation to Do Well in Class, and Interest in Class

Variable	Actual academic Internet use	Actual nonacademic Internet use	ACT score	Motivation	Interest
Final-exam score	.09	−.25*	.36*	.33*	.26*
Interest	.09	−.19†	−.10	.43*	—
Motivation	.15	.01	.00	—	
ACT score	−.06	.07	—		

†$p < .10$. *$p < .05$.

Table 3. Correlations Between Cumulative Final-Exam Score and Actual Nonacademic Internet Use for the Seven Site Categories

Nonacademic Internet use	Final-exam score
Using social media	$-.23^{*}$
Shopping	$-.19^{\dagger}$
Reading e-mail	$-.13$
Chatting	$-.01$
Reading news and sports	$-.10$
Watching videos	$-.27^{*}$
Playing games	$-.14$

$^{\dagger}p < .10$. $^{*}p < .05$.

findings more closely, we performed a median split on ACT scores (high-score group: $n = 33$; low-score group: $n = 37$) and assessed Internet use for each group. Our data did not support the idea that students with greater intellectual capability were better multitaskers. In fact, the magnitude of the negative relationship between laptop use and exam score was twice as large for students with high ACT scores, $r(31) = -.44$, $p < .01$, as for students with low ACT scores, $r(35) = -.16$, $p = .33$. The difference between the two correlations was tested with a Fisher's r-to-z transformation but was not significant, $z(69) = 1.24$, $p = .22$. In sum, the relationship between laptop Internet use and final-exam performance was similar across the two levels of intellectual ability.

Types of nonacademic Internet use and classroom learning

Internet use was classified to seven categories according to type of site visited and then correlated with final-exam score. Although all the correlations were negative, only two were significant: those for social media and video sites. The correlation for online shopping approached but did not reach significance, $r(82) = -.19$, $p = .08$ (Table 3). The hierarchical regression model was also used to assess whether the correlations would account for variance in final-exam score when we controlled for the impact of the participant's motivation, interest, and intelligence (i.e., composite ACT score). Introducing the combined measure of social-media browsing (instead of total Internet use) to the original regression model at Step 2 explained an additional 8.1% of the variation in the final-exam score, and this change in R^2 was significant, $F(1, 57) = 6.52$, $p < .05$. Introducing online-video watching to the original regression model at Step 2 explained an additional 6.2% of the variation in the final-exam score, and this change in R^2 was also significant, $F(1, 57) = 4.84$, $p < .05$.

Perception of Internet use and learning

As in previous studies (Clayson & Haley, 2013; Tindell & Bohlander, 2012), students rated their laptop use as having little or no effect on their classroom learning; the average response was 3.68 ($SD = 0.73$) on a 5-point scale (1 = *it helped learning*, 3 = *no effect*, 5 = *it disrupted learning*). The same was true when people rated the effect on their own learning of viewing other students' laptop use ($M = 3.43$, $SD = 0.72$). Composite ACT scores were not related to either of these ratings, $r(62) = -.05$, $p = .67$, and $r(60) = -.11$, $p = .40$, respectively. Further, participants in the high-score ($M = 3.70$, $SD = 0.64$) and low-score ($M = 3.74$, $SD = 0.73$) ACT groups gave similar ratings for the relationship between their Internet use and learning, $t(62) = 0.26$, $p = .79$. In addition, the high-score ($M = 3.42$, $SD = 0.56$) and low-score ($M = 3.48$, $SD = 0.92$) ACT groups gave similar ratings for the relationship between the effect of viewing other students' use and learning, $t(60) = .33$, $p = .74$.

To assess more closely how beliefs about Internet use and learning were related to the actual relationship, we separated participants into two groups: those who rated their Internet use as having no effect on their learning (i.e., a rating of 3; $n = 25$) and those who rated their Internet use as having a somewhat disruptive effect on their learning (i.e., a rating of 4; $n = 45$). The other rating categories each had fewer than 7 participants and were not analyzed further. Students who said their Internet use had no effect on their learning had a near-zero correlation between Internet use and final-exam grade, $r(23) = .02$, $p = .91$, collapsed across categories. In contrast, those who rated a disruptive effect had a significant, negative correlation, $r(43) = -.31$, $p < .05$. Moreover, students who rated their Internet use as having no effect on classroom learning had better exam grades than students who rated their Internet use as slightly disruptive, $t(68) = 2.39$, $p < .05$. Students who rated their Internet use as having no effect on classroom learning used the Internet less than did students who rated their laptop use as having a disruptive effect, $t(68) = 2.35$, $p < .05$. Thus, students accurately reported the effect of their Internet use on their learning, and the knowledge of a disruptive effect was related to higher laptop use rather than lower use. However, it should be noted that responses to this survey were collected at the end of the semester, so students were aware of their prior exam scores.

Self-reported nonacademic use versus actual use. We next compared participants' estimates of their nonacademic Internet use during a typical class with their actual use. To do this, we correlated the number of minutes of Internet use that students reported on the survey with their actual duration of Internet use as determined via the proxy server. We used duration rather than the number of requests or our calculated combined variable because duration information was more available to the students. In contrast, requests to download information happen both actively and passively. Students may remember the number of times they opened a particular site but would be unaware of how many download requests that actually entailed. Because the survey specifically asked students for duration of Internet use, the actual duration is the most relevant variable to compare. Seventy-nine participants completed the self-report survey questions regarding Internet use. To reduce positive skew, we square-root-transformed survey data and actual duration data.

We found that our participants were accurate in their estimation of Internet use, and most measures were strongly correlated. Thus, students who actually used the Internet more also reported using the Internet more. This was true for social media use, $r(77) = .66$, $p < .001$, online shopping, $r(77) = .48$, $p < .001$, reading news articles, $r(77) = .63$, $p < .001$, reading sports articles, $r(77) = .28$, $p < .05$, and online gaming, $r(77) = .49$, $p < .001$. However, estimates for online video, $r(77) = .07$, $p = .55$, were less accurate and did not have significant correlations.

We also asked students to rate the percentage of time in class that they used their laptops for non-class-related purposes, and this was also proportional to actual totals of Internet time, $r(76) = .26$, $p < .05$. The estimates in terms of absolute time were also close. Participants estimated that, on average, they used the Internet for non-classroom purposes between 25% and 29% of the total class time. This corresponds to the actual class average of 37 min, or 37% of class time (excluding break). The students' estimates of the number of minutes they engaged in each type of Internet activity were also relatively close to their actual use. For example, the median time that students reported browsing social-media sites was 15 min, whereas our measure of actual browsing time was 6 min (note that our estimates of actual use are conservative because we did not pad time for viewing after the final request). In sum, the students were surprisingly accurate when reporting Internet use.

For students with high ACT scores, there was a reliable, strong correlation between estimates of percentage of online laptop use during class and actual duration of time spent online, $r(31) = .45$, $p < .01$, whereas for students with low ACT scores, there was no relationship, $r(29) = .09$, $p = .64$. However, this was true only when students were asked to estimate a percentage: The correlations between estimated and actual duration of online laptop use were similar for students with low ACT scores and those with high ACT scores. For example, for social-media use, the two groups had similar correlations—high-score group: $r(31) = .55$, $p = .001$; low-score group: $r(30) = .69$, $p < .001$. These results indicate that framing questions about online laptop use in terms of minutes of class time rather than percentage of class time will yield better estimates of actual online laptop use. Estimating a percentage requires additional math operations that may be more difficult for individuals with lower cognitive ability.

Self-reported smartphone and tablet usage. The focus of the present study was on recording and examining actual laptop Internet use in class; however, we also asked participants to self-report their smartphone and tablet use. The proxy server monitored only laptops, so smartphone and tablet use was unmonitored. The students self-reported using their smartphones or tablets in addition to their laptops in order to text ($M = 27$ min) and check social media ($M = 19$ min), as well as to perform other functions.

Discussion

The present study is one of the first in which objective measures of classroom Internet use for academic and nonacademic purposes were tracked and the relationship between actual Internet use and intelligence, motivation, and interest was assessed. We found that nonacademic Internet use was frequently observed and was inversely related to performance on the cumulative final exam. This relationship was observed regardless of interest in the class, motivation to succeed, and intelligence. Moreover, accessing the Internet for academic purposes during class was not related to a benefit in performance. Collectively, these findings raise questions about whether students should be generally encouraged to bring their laptops to class without regard to their necessity for classroom activities.

Previous research has shown that students underplay the relationship between classroom learning and Internet use for nonacademic purposes during class. Our correlations, instead, suggest that Internet use has a small-to-medium association with exam scores (Cohen, 1988). In the present study, we sought to understand this disconnect. Our results provided no support for the idea that students attribute their classroom performance to an underlying factor that may also influence their Internet use, such as boredom or low motivation to do well. Although these factors were related to classroom performance, they were not reliably related to Internet use. Moreover, the relationship between nonacademic Internet use and performance remained when these factors were accounted for in a hierarchical regression model.

We also ruled out the explanation that more intelligent students are better able to multitask. Internet use was associated with lower final-exam scores even when we controlled for ACT scores. In addition, the inverse relationship between Internet use and final-exam scores was similar for individuals with high and low ACT scores (identified by a median split).

The idea of a disconnect between the perceived and actual relationship of Internet and classroom learning is based on average group ratings. When we examined individuals who rated Internet use as having "no effect" separately from those who rated Internet use as having a "slightly disruptive effect," we found that students had accurate knowledge about how their Internet use affected their learning. Students who believed that their classroom learning was not affected by their Internet use showed no relationship between Internet use and final-exam score; those who believed that their use had a slight effect showed a medium effect size for the relationship between Internet use and final-exam score. Moreover, students who rated their Internet use as having a "slightly disruptive effect" had lower exam scores and used the Internet more than the other group. Thus, students had insight into their own Internet use.

Why did students with insight into the disruptive relationship between Internet and learning still misuse the Internet? One possibility is that because the rating came at the end of the semester, students may not have been aware of this relationship beforehand. Given the large sample of freshmen for whom this may have been their first college class, they may not have had previous experience using the Internet in class and realized only after the term ended that it negatively affected learning. If so, the relationship between Internet use and exam score should be higher for freshmen (n = 46) than sophomores (n = 30). This was not the case because the correlation was numerically larger for sophomores, $r(28) = -.35$, p = .06, than for freshmen, $r(44) = -.25$, p = .10.

Alternatively, students may have been aware that their Internet use was disruptive but could not inhibit this behavior. Neural and behavioral markers of Internet addiction are similar to those of other types of addiction, such as gambling or substance addictions (Dong, DeVito, Du, & Cui, 2012; Turel, He, Xue, Xiao, & Bechara, 2014). In one study, individuals addicted to Facebook (compared with those not addicted to Facebook) made more false alarms in response to the Facebook logo in an inhibitory control task and showed activity in the reward centers of the brain when the logo appeared (Turel et al., 2014). It is possible that students who claimed that Internet use had no effect on their learning were better able to control their browsing behavior and therefore browsed less. In contrast, those who were unable to inhibit their Internet use may have known that it was distracting but felt compelled to use it anyway. A recent study provides some support for this hypothesis; people who engaged more heavily with mobile devices were less able to delay gratification and had a greater tendency for impulsive behaviors (Wilmer & Chein, 2016). Further work is needed to understand whether students who rated their use as having a disruptive effect are using the Internet because of a compulsion to do so.

Students also used their laptops for such academic purposes as logging on to the class Web site and searching for extra information on Wikipedia. This type of use was similar to a study showing that student laptop use in a learning environment was limited to passive processing of information (Kvavik, 2005). We found no association between academic use and classroom learning; this is consistent with the idea that although students are highly familiar with technology, they are not necessarily using technology in the most effective way (Kirschner & Karpinski, 2010; Kvavik, 2005). Indeed, students may take lecture notes on the PowerPoint slides that they have downloaded, but writing notes by hand has been shown to be better for learning (Mueller & Oppenheimer, 2014).

The use of a proxy server to track Internet use had several benefits but also some disadvantages. One benefit is that the students did not need to download tracking software on their computers, and this may have increased enrollment for two reasons: First, given the variety of computers and operating systems used by students (Gould, Cox, & Brumby, 2016), potential problems with installing software were avoided. Second, students may have felt more comfortable knowing that their Internet use was not being tracked when they logged out of the proxy server compared with the lower transparency of tracking software. On the other hand, the proxy server did not track non-Internet laptop use such as word-processing software or spreadsheet programs. Future studies should determine how using such software during class affects learning.

In a previous study, students underestimated their Internet use (Kraushaar & Novak, 2010); in the current study, students' reports were essentially consistent with their actual use, especially in terms of the relative durations between categories of Internet use. Although the self-report data seem to overestimate use, our objective measure is likely to underestimate use given that we did not pad durations by any additional time after the last request. This suggests that self-report may be a viable way to measure portable device use when tracking is not feasible.

In conclusion, we found that there was no disconnect between students' beliefs and the actual relationship between Internet use and classroom learning. Students who thought their Internet use had no effect showed no effect, whereas those who rated it as slightly disruptive showed a negative effect. The relationship was not accounted for by intelligence, motivation to do well, or interest in class material. Students using the Internet for nonacademic purposes may be unable to inhibit Internet browsing even though they believe it to be harmful to their learning. The lack of an associated benefit when browsing class-related Web sites and the detrimental relationship associated with nonacademic Internet use raises questions regarding the policy of encouraging students to bring their laptops to class when the laptops are unnecessary for class activities.

Action Editor

Marc J. Buehner served as action editor for this article.

Author Contributions

All the authors contributed to the study concept and design. Data acquisition was performed by M. G. Uitvlugt and K. M. Fenn. S. M. Ravizza and M. G. Uitvlugt performed the data analysis and drafted the manuscript. K. M. Fenn provided critical revisions. All the authors approved the final version of the manuscript.

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The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797616677314

Notes

1. The proxy server was compatible with all major Internet browsers (i.e., Safari, Firefox, Chrome, and Internet Explorer).
2. Although e-mail can be checked outside of an Internet browser, 86% of the participants used a Web site to check e-mail, and the majority used the campus-based e-mail Web site (i.e., mail.msu.edu).

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