Examining the Affects of Student Multitasking With Laptops During the Lecture

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ABSTRACT

This paper examines undergraduate student use of laptop computers during a lecture-style class that includes substantial problem-solving activities and graphic-based content. The study includes both a self-reported use component collected from student surveys as well as a monitored use component collected via activity monitoring "spyware" installed on student laptops. We categorize multitasking activities into *productive* (course-related) versus *distractive* (non course-related) tasks. Quantifiable measures of software multitasking behavior are introduced to measure the *frequency* of student multitasking, the *duration* of student multitasking, and the *extent* to which students engage in distractive versus productive tasks.

We find that students engage in substantial multitasking behavior with their laptops and have non course-related software applications open and active about 42% of the time. There is a statistically significant inverse relationship between the ratio of distractive versus productive multitasking behavior during lectures and academic performance. We also observe that students under state the frequency of email and instant messaging (IM) use in the classroom when self-reporting on their laptop usage.

Keywords: Multitasking, Distraction, Lecture, Laptop, Classroom, Cognitive, Teaching, Learning

1. INTRODUCTION

Laptop computers are widely used in many college classrooms today (Weaver and Nilson, 2005); however, there is an ongoing debate regarding the purpose and value of laptop initiative programs that encourage or even require students to purchase laptops, and the role of laptops in classrooms. Although the use of laptops in the classroom has the potential to motivate and contribute to student learning (Efaw, Hampton, Martinez, Smith, 2004; Trimmel and Bachmann, 2004), they also have the potential to negatively impact student attention, motivation, student-teacher interactions, and academic achievement (Young, 2006; Meierdiercks, 2005).

Previous research has shown that students who bring laptops to class often engage in electronic multitasking that involves switching their cognitive focus back and forth between tasks that are directly related to the lecture material and tasks that are not directly related to the lecture material (Fried, 2008; Hembrooke and Gay, 2003; Grace-Martin and Gay, 2001). Although many students may believe they can switch back and forth between different tasks with no serious consequences to their academic performance, multitasking has been shown to dramatically increase the number of memory errors and the processing time required to "learn" topics that involve a significant cognitive load (Rubenstein, Meyer, and Evans, 2001). Attempting to "learn" while engaged in multitasking behavior can result in the acquisition of less flexible knowledge that cannot be easily recalled and/or applied in new situations (Foerde, Knowlton, and Poldrack, 2006). Furthermore, it takes time and effort to refocus after switching from one task to another (Bailey and Konstan, 2006).

It can be argued, that multitasking is a natural part of the modern classroom and work environments and students need to learn to multitask effectively – especially in today's high tech world. Research that investigates how students use laptops in the classroom and what affects laptop usage has on performance outcomes does exist, but there is a lack of research that focuses on the unstructured or unsanctioned use of computers in the classroom, that explicitly measures learning outcomes, and that incorporates actual use data[1]. In general, multitasking has been shown to negatively impact productivity (Foerde, Knowlton, and Poldrack, 2006; Rubenstein, Meyer, and Evans, 2001); however, the affects of different types of computer-based multitasking behaviors in the classroom have not been measured and examined in detail to date.

This paper presents the results of an exploratory study that investigates different types of student multitasking behavior while using laptop computers in an unstructured manner during class. A number of novel contributions are made. First, we collect both self reported laptop usage data and actual laptop usage data from spyware installed on student laptops. This allows us to directly measure student laptop use, and then compare student's actual usage to self-reported usage. Second, we categorize different types of software multitasking activities and identify which activities are performed most frequently and for how long. We then examine how different categories of distractive software activity impact class performance. We define *distractive multitasking* as tasks or activities where cognitive resources are used to process information that is not directly related to the course material. *Productive multitasking* is defined as tasks or activities that are directly related to completing a primary task associated with the course material. Finally, we introduce quantifiable metrics for measuring the frequency, duration, and extent of student multitasking behavior in class, and evaluate the impact this behavior has on academic performance.

Three primary research questions are addressed. (1) How does the *frequency* of multitasking related to each multitasking category affect learning outcomes? (2) How does the *duration* of time students spend in each multitasking category impact learning outcomes? (3) How does the *extent* of time spent between distractive multitasking and productive multitasking affect learning outcomes?

2. BACKGROUND LITERATURE

In recent years, research related to the student use of technology, and specifically the use of laptops in the classroom has grown considerably (Fried, 2008). Many educators struggle with the question of what role laptops should play in the classroom and are actively involved in developing strategies to maximize the positive impacts while minimizing the negative impacts (Adams, 2006). The literature discusses a number of classroom control strategies for laptop usage in the classroom which range from unlimited use to outright bans (Plymale, 2007; Young, 2006; Meierdiercks, 2005). The question of how laptops should be used in the classroom, or whether they should be used at all, is complicated by the fact that some universities and colleges have administrative policies that encourage or even require students to purchase laptop computers (Yamamoto, 2007).

Driver (2002) found that laptops with Web based activities enhanced student satisfaction with the course. This study relied on student perceptions regarding the value of laptops with respect to interaction and did not consider learning outcomes. Finn and Inman (2004) found that alumni and current students were generally pleased with their campus laptop initiative program, but did not consider learning outcomes. Fried (2008) reported that higher laptop use in the classroom lead to an increase in multitasking and distraction, a decrease the understanding of course material, and negatively impacted academic performance. This study relied on self-reported student use of laptops. Golub (2005) noticed that some students tended to play games, browse unrelated Web sites, and check email with their laptops during class, but there was no link to learning outcomes. Barkhuus (2005) observed distractive laptop use during the lecture that was confirmed by student self-reports. Unfortunately, this study suffered from a serious self-selection bias and a low response rate. Grace-Martin and Gay (2001) looked only at Web browsing both in and out of class and found that the length of browsing sessions in class had a negative correlation with the overall course grade. Hembrooke and Gay (2003) examined the impacts of multitasking on learning and determined that student Web browsing during lectures led to a whole letter grade decrement (10%) in recognition and recall measurements collected at the end of each lecture.

3. THE IMPACT OF MULTITASKING ON MEMORY

Cognitive scientists define *memory* as the ability to store, retain, and retrieve information. Memory can be categorized as sensory, working, and long-term. *Sensory memory* lasts only a few seconds and involves the very brief storage of information processed through the senses such as smell, sight, and sound. *Working memory* temporarily stores and manages the information that is needed to carry out complex cognitive tasks like reasoning, learning, and comprehension. Working memory is involved in initiating, selecting, and terminating information processing activities like storing and retrieving data. The capacity of the working memory is limited but the contents of working memory can be transferred to *long-term memory*, a system for permanently storing and managing information. Long-term memory has an unlimited capacity that decays slowly (Ericsson and Kintsch, 1995).

Cognitively, the primary task for students during class is to process the information being presented during the lecture and "learn" the material. Learning requires a combination of overlapping activities such as listening, viewing, formulating and answering questions, and note taking. Depending on the subject matter being covered and the clarity of the lecture, learning new material can involve a substantial cognitive processing effort. While routine or familiar tasks can be often be performed with relatively little cognitive effort, more complex, new, or unfamiliar tasks pose a cognitive processing load that may exceed the capacity of an individual's working memory. If this happens, some of the primary information will not be encoded in long-term memory and will be lost.

While engaged in a distractive task, a primary task can go cognitively unattended. This leads to weaker short term memory encodings that may not be adequately transferred to long term memory. Additional cognitive resources are also required when attention is moved from a distractive task back to the uncompleted primary learning task in order to reorient. When cognitive resources are demanded by reorientation and / or by distractive tasks, primary tasks may not receive the cognitive resources they need – leading to increases in learning errors, learning times, annoyance, and anxiety (Bailey and Konstan, 2006). This directly relates to the classroom environment and the use of laptops in the classroom from the standpoint that even if students have course-related material "open", switching back and forth between various tasks, and particularly between course-related and non course-related tasks, may negatively impact learning.

4. METHODOLOGY AND DATA COLLECTION

This research project involves collecting data based on both actual student usage as reported by monitoring software (spyware) installed on student laptops and self-reported usage data provided by the students[2]. The study participants are 97 undergraduate students from three different sections of a junior-level, required course in management information systems (MIS) taught during the fall 2006 semester at The University of Vermont (UVM). At the time the study was conducted, The School of Business Administration (SBA) at UVM had a laptop computer requirement and all students were required to bring a laptop to each MIS class loaded with a standard Microsoft Office software bundle that included Access, Excel, Internet Explorer, Journal, Outlook, PowerPoint, Visio, and Word. Most students participating in the study had owned their laptop for two or more years. All students had passed a required first year course that included the use of Microsoft Office suite applications to solve business problems.

The research test bed course was taught in a standard "sage on the stage" lecture hall with a gently sloping, semi-circular audience area, a seating capacity of 55 students, and hard-wired and wireless network access to every seat. The room included a lectern with a computer and projection system connected a large screen display. The course was taught in a traditional lecture style, met twice a week for 75 minutes over a 15 week semester, and was taught by two experienced educators. The course emphasized graphical modeling and problem solving skills and the subject matter included process modeling with data flow diagrams, data modeling with entity relationship diagrams and data base design, and data base implementation using Microsoft Access. Hardware/software basics and an introduction to the classic system development life cycle completed the list of topics covered. The learning objectives for the course spanned all six of Bloom's revised taxonomy of cognitive objectives including remembering, understanding, applying, analyzing, evaluating, and creating (Anderson and Krathwohl, 2001).

Demographic and academic performance data were collected for each study participant using the university's student record keeping system. The demographic variables included student gender, grades in three prerequisite courses, cumulative grade point average (GPA), the scholastic aptitude test (SAT) mathematics and verbal scores, and a UVM admission score. During the first week of the study course, an in-class pre course technology readiness assessment (TRA) examination was administered to all students. The technology TRA included 50 questions to be answered in 40 minutes. The assessment tool used performance based testing questions with simulated Microsoft Office products in addition to traditional multiple choice questions, to measure software skill levels and computer literacy. Student performance data from the test course were collected by the course educators and included student scores for a final project, two semester exams, a final comprehensive exam, the homework average, and average for in-class quizzes.

Data from each of the two educators and three class sections were examined for self-selection bias. We found no significant differences attributed to course section or educator as measured by a one way analysis of variance (ANOVA) at the 0.05% level with respect to gender, mean cumulative GPA, math SAT, verbal SAT, or UVM Academic Composite Evaluation (ACE)[3] student admission scores. There were no significant differences between the different course sections or the different educators that were attributed to student reported mean years of computer experience, reported mean hours of PC usage per week, mean prerequisite course grades for the first year required MIS course or the required sophomore financial and management accounting courses, or in pre-course computer literacy as measured by our TRA exam. Results are shown in Table 1. All statistical analyses are performed using the statistical package for social sciences (SPSS) software.

Both educators and all three course sections had similar questionnaire response rates between 81% and 100%. Based on these results, it does not appear as though students exhibited a self-selection bias while registering for either course section or educator. Subsequently, the data from all three class section and the two educators were combined into a single sample.

Variable Tested	Between 3 Course Sections	Between 2 Educators
Gender	.422	.758
Cumulative GPA	.940	.752
Math SAT score	.686	.438
Verbal SAT score	.947	.867
University Admission score (ACE)	.875	.716
Self-Reported Years of Computer Experience	.286	.555
Self Reported Weekly PC use	.874	.784
Computer Literacy Score (TRA)	.482	.232
Prerequisite MIS Course Grade	.349	.626
Prerequisite Financial Accounting Course Grade	.679	.996
Prerequisite Managerial Accounting Course Grade	.248	.579

Table 1. One Way ANOVA Significance for Differences between Course Sections and Educators

4.1 Self-Reported Laptop Use

Information on student perceptions of the SBA's laptop requirement and how they used their laptops in class was collected via survey. The survey consisted of 27 questions divided into 5 sections. The first section focused on the type of laptop each student used, how reliable they believed the laptop to be, and the level of satisfaction with the laptop. Section two addressed how frequently students used their laptops in the research test bed course. The third section collected information on student laptop use in all other university courses. The fourth section addressed how often students used specific software packages including Microsoft One-Note, Visio, Access, Excel, Outlook, etc., as well as their use of general software categories including instant messaging (IM), media sharing, media playing, and gaming. Students reported the hours per week they used their laptops and how long they had owned it in the final section. They also provided their perceptions of the overall value of their laptop and whether the SBA should continue to require students to purchase laptops.

Most survey questions were measured on a five point scale (1=never in any lecture, 2=a little in a few lectures, 3=a little in every lecture, 4=a lot in a few lectures, and 5=a lot in all lectures). The only survey question germane to this study, was a multiple response question that asked students whether they used their laptops for Email, instant messaging, note taking, surfing the Web, or playing games during the test bed class lectures. Using survey response information we were able to compare the self-reported and spyware recorded use for the email and IM categories. Unfortunately, we could not make direct comparisons to the other active window categories discussed in Section, 4.2.

Students were given an extra credit quiz grade to motivate participation in the survey and were verbally encouraged to fill out the questionnaire completely and carefully. The survey questionnaire was completed during the last class meeting of the semester by 90 of the 97 students enrolled in the class for a 93% response rate.

4.2 Monitored Laptop Use

Students were given the opportunity to participate in the monitored use component of the study on a volunteer basis. Students who installed and used the spyware to record their actual laptop use during the class were given an additional extra credit quiz grade for participation. During the first class meeting of the semester the monitoring component of the research project was discussed, and the students were told of the rewards for participating in the study, the types of information that would be collected, and how the information would be used. A procedure to maintain anonymity of their recorded data was also explained. The students were also reminded that they were expected to follow the acceptable usage policies outlined by university network services and while in class they were expected to pay attention and participate in the lecture. The students were then given time to take home and review a written description of the study and the corresponding research participation agreement and to ask any questions they may have. During the third class meeting of the semester, students wishing to participate in the study installed the Activity Monitor™ spyware package from SoftActivity and completed a signed university human subject agreement.

When Activity Monitor™ was running, the software logged a data record with the user name, computer name, program name, executable file (.exe) name, window/page name, and the start date/time for each new software application window that received the focus. The Activity Monitor™ software calculated the duration time that each new application window was active before being replaced by the next window to receive the focus.

An *active window* is the object that is currently displayed on the laptop monitor and is considered to be "on top" or having the "focus". The active window is the window currently waiting for and / or receiving mouse and keyboard input. An *active program* is the program that is currently running the active window. An active program can generate many windows but only one window has the focus (i.e. is active) at any given time. For example, if a computer is running multiple instances of Internet Explorer (IE), IE is the active program, but only one instance (i.e. a particular Web page) of IE has the focus at a given time – the one that is active. The Activity Monitor™ software also recorded all key-strokes made by the student as well as the uniform resource locator (URL) of each Web site visited. Students received verbal reminders to turn the spyware on at the beginning of the lecture and off at the end.

A list rubric was developed to classify each active window into one of two multitasking categories, 1) productive and 2) distractive. All active windows related to the course material were classified as productive while active windows that were not related to the course material were classified as distractive. The distractive windows were further subdivided into 2a) surfing and entertainment, 2b) email, 2c) IM, 2d) PC operations, or 2e) miscellaneous categories as shown in Table 2.

Multitasking Category	Application Examples / Explanation
1) Productive course material-related windows	MS Office applications related to the course material and course-related Web browsing
2) Distractive non-course material-related windows:	
2a) Surfing & Entertainment	Non-course-related Web surfing, games, media sharing, pictures, etc.
2b) Email	MS Outlook and Web-based email applications
2c) Instant Messaging	AOL, AIM, MSN, Yahoo, etc.
2d) PC Operations	System software, tuning & procedural steps, Windows Explorer
2e) Miscellaneous	Unable to determine

Table 2. Classification of Monitored Software Activities by Multitasking Categories

It was possible for students to generate a mix of productive and distractive active windows even when only one active program was involved. For example, using a browser to view an active window containing a course-related PowerPoint slide would be considered productive, while viewing an active window for a Web site that was unrelated to the course would be considered distractive. Classifying active windows generated by a Web browser required an examination of the URL associated with the Web page. If the URL of the active window was course-related, then the activity was classified as productive. If the URL was unrelated to the class, such as a news or sports page, then it was classified as distractive surfing and entertainment. Active windows generated by the 3D Pinball program and other games were also classified as distractive surfing and entertainment activities. Active windows generated by email applications or Webmail were classified as distractive email. Active windows generated by an Instant Messenger program such as AOL were classified as distractive IM.

The PC operations subcategory included active windows related to Windows Explorer, Control Panel, and Command Prompt; and captured activities associated with locating and/or downloading files, performing file management, and tuning the computer for better performance. These active windows are necessary for computer use, but are not directly related to the course material and represent a distraction. If the multitasking category could not be determined, the active window was classified as a miscellaneous activity. While the categorization of the various computer-based tasks / activities is not perfect, Activity Monitor™ provided enough detailed information to categorize the majority of active windows. Only 6.1% of all active windows were classified as miscellaneous.

During the last week of classes, student spyware logs were collected from 45 of the 97 students for a monitored use response rate of 46%. Before the final course grades were calculated, each student activity log was exported to a spreadsheet log file and any active window records from outside of the course lecture dates and times were removed. Four of the 45 student spreadsheet log files were eliminated from the analysis because they contained less than 25 minutes of spyware monitoring during any lecture. While somewhat arbitrary, we decided that students who recorded their activities for less than a third (25/75 minutes) of a lecture did not have enough monitoring time to be representative. The final student response rate for spyware monitoring data was 42% (41/97).

Student user names were replaced by a 4 digit code to maintain anonymity. Each record in the spyware spreadsheet was then classified into productive and distractive categories following the rubric. Microsoft Excel pivot table functions were used to "roll-up" the active window records into a new summary spreadsheet file with one data record per student, so each student record contained the total number and duration for each active window in each of the six multitasking categories.

There was some initial concern that students with very self-distracting laptop usage habits might choose not to record their laptop usage during lectures out of embarrassment or fear of educator punishment due to the content of the activity log files. If a "fear-of-punishment / embarrassment" bias occurred, the sample of 41 students would not properly represent the full spectrum of in-class laptop users[4]. The results of an independent *t*-test comparing students who used Activity Monitor™ to students who did not use Activity Monitor™, found no significant differences in the mean values for percent female, cumulative GPA, math and verbal SAT scores, and university admission scores at the 0.10 level. There were no significant differences in mean computer literacy scores measured at the start of the semester; nor any differences in the mean self-reported years of computer experience and usage per week between those students who used Activity Monitor™ and those who did not use Activity Monitor™. Finally, there were no statistically significant differences in either the managerial or financial accounting prerequisite mean course grades. Results are shown in Table 3.

There was plenty of anecdotal evidence of unsanctioned use in the keystroke logs, indicating that at least some of the students did not shut down Activity Monitor™ even when they were engaged in "inappropriate" behavior. For example, keystroke logs showed that some students used IM to pass crude comments about educator competencies and their classmates' social activities. Other students freely browsed the Web and made online purchases during class.

Based on these observations, we concluded that there was no evidence of a self-selection bias or fear-of-punishment/embarrassment non-response bias caused by students who chose not to participate in Activity Monitor™, or who turned off Activity Monitor™ when they were engaged in "inappropriate" behavior.

Variable Tested	Students Monitoring Mean (Std Error)	Students Not Monitoring Mean (Std Error)	Significance (2 tailed)
Percentage Female	.59 (.08)	.66 (.05)	.461
Cumulative GPA (max 4.0)	2.87 (.50)	2.79 (.06)	.373
Math SAT score (max 800)	583. (8.1)	584 (9.0)	.942
Verbal SAT score (max 800)	550. (9.9)	548 (8.9)	.874
University Admission score (max 9)	5.76 (.31)	6.19 (.23)	.256
Reported Years of Computer Experience	6.8 (.47)	7.1 (.37)	.615
Self Reported Weekly PC use (hours)	21.9 (1.4)	22.3 (1.3)	.863
Computer Literacy at Start of Class (max 100 points)	84.6 (1.5)	81.1 (1.4)	.106
Prerequisite Financial Accounting Course Grade (max 4.0)	2.52 (.11)	2.51 (.84)	.942
Prerequisite Managerial Accounting Course Grade (max 4.0)	2.59 (.13)	2.50 (.11)	.607

Table 3. *t*-Test for Mean Differences between Students Using and Not Using Activity Monitor™

It is important to note that if a systematic "fear of punishment/embarrassment" bias did occur, the study results would under report distractive use.

5. RESULTS

Existing literature has shown that multitasking can negatively impact performance (Foerde, Knowlton, and Poldrack, 2006; Rubenstein, Meyer, and Evans, 2001). We apply this finding to our research examining the student use of laptops in the classroom and develop the following hypotheses:

1. Students with a high frequency of software multitasking during lectures will exhibit lower academic performance than students with a low frequency of software multitasking.
2. Students with longer software multitasking durations during lectures will exhibit lower academic performance than students with shorter software multitasking durations.
3. Students with higher ratios of distractive software multitasking to productive software multitasking during lectures will exhibit lower academic performance than students with lower ratios.

The results are organized into four sections. Section 5.1 presents an analysis of multitasking frequency during the lecture. Section 5.2 discusses the duration of both productive and off-task (i.e. distractive) multitasking. We examine how students allocate their laptop use between distractive and productive software multitasking activities in Section 5.3. The final section – Section 5.4 – compares some of the usage data we collected via Activity Monitor™ to the self-reported survey usage data provided by the students.

5.1 Multitasking Frequency

We measure the frequency of multitasking by determining the total number of new active windows generated during a lecture. The generation of a large number of active windows is synonymous with a high frequency of multitasking. We introduce the Software Multitasking (SMT) rate to measure the frequency of multitasking behavior. The student SMT rate is the total number of active windows generated by the student divided by the number of lectures monitored by the student as shown in (1). Students with higher SMT rates are engaged in more frequent multitasking during the lecture than students with lower SMT rates. We calculate each student's SMT rate for both primary multitasking categories (productive and distractive) and all five subcategories of distractive software.

$$SMT\ rate = \frac{Num\ of\ Active\ Windows}{Total\ Num\ of\ Monitored\ Lectures} \qquad (1)$$

Table 4 summarizes student software multitasking (*SMT*) rates by multitasking category. Students generated 65.8 active windows per lecture on average, and also averaged more distractive windows (40.7) per lecture than productive windows (25.1) per lecture. The distractive multitasking category is further broken down into surfing and entertainment, email, IM, PC operations, and miscellaneous categories where the mean student SMT rates were 6.2, 5.1, 8.7, 17.4, and 3.2 windows per lecture respectively.

Multitasking Category	Mean SMT Rate	SMT Rate Std. Error	Min SMT Rate	Max SMT Rate
Overall	65.8	5.9	21.0	173.7
Productive	25.1	3.1	7.5	122.7
Distractive	40.7	4.3	10.0	121.4
Surfing & Entertainment	6.2	1.3	0.0	47.4
Email	5.1	0.7	0.0	20.0
IM	8.7	2.7	0.0	86.0
PC Operations	17.4	1.3	5.3	50.1
Miscellaneous	3.2	0.5	0.0	10.5

Table 4. Analysis of Student SMT Rates by Software Multitasking Category

At least one student generated 173.7 windows per lecture while at least one other student generated only 25.7 windows per lecture. There was also variability in productive and distractive SMT rates. At least one student generated 122.7 productive active windows per lecture while at least one other student generated only 7.5 windows per lecture. At least one student had a distractive *SMT rate* of 121.4 windows per lecture and at least one other student had a distractive *SMT rate* of 11 windows per lecture.

Table 5 presents the Pearson correlation coefficients between student SMT rates and academic performance at the .05 level for each software use category. We found *limited* support for hypothesis (1): students with a high frequency of multitasking will exhibit lower academic performance than students with a low frequency of multitasking, as measured by the SMT rate. Students with higher SMT rates for IM multitasking were significantly correlated at the .05 level with lower quiz averages, project scores, and final exams scores. Students with higher SMT rates for PC Ops were positively and significantly correlated with quiz average at the .05 level.

5.2 Multitasking Duration

We measure the duration of each active window by subtracting the laptop's clock time when the window becomes the *active* window from the laptop clock time when the window loses focus and is replaced by the next active window. The window duration measures the amount of time that an active window has the focus and *can* be easily viewed by a student. To explore the affect that active window durations have on academic performance we introduce the Window Duration Potential (WDP), which is a proxy measure for the total time (in seconds) a student actually spends viewing the active windows they generate as shown in (2). We calculate each student's WDP for both primary multitasking categories (productive and distractive) and all five subcategories of distractive multitasking.

$$WDP = \frac{Total\ Time\ Windows\ Active\ (in\ sec)}{Num\ of\ Windows\ Generated} \qquad (2)$$

Multitasking Category	Academic Performance Measures						
	HW Ave.	Quiz Ave.	Project	Test #1	Test #2	Final Exam	Final Course Ave.
Overall	.039 (.809)	.120 (.461)	-.111 (.560)	.037 (.820)	.097 (.558)	-.007 (.969)	.093 (.569)
Productive	.247 (.124)	.304 (.057)	.083 (.664)	.102 (.532)	.291 (.073)	.224 (.170)	.252 (.116)
Distractive	-.128 (.430)	.058 (.722)	-.229 (.224)	-.024 (.885)	-.083 (.614)	-.178 (.278)	-.058 (.723)
Surfing & Entertainment	-.027 (.868)	.109 (.504)	.031 (.871)	.030 (.855)	.024 (.883)	.015 (.929)	.092 (.573)
Email	.053 (.747)	.076 (.640)	.046 (.811)	-.072 (.659)	-.009 (.958)	.094 (.570)	.080 (.622)
IM	-.278 (.082)	**-.335* (.034)**	**-.388* (.034)**	-.180 (.267)	-.294 (.069)	**-.416** (.009)**	-.301 (.059)
PC Ops	.233 (.148)	**.374* (.017)**	.030 (.876)	.272 (.090)	.275 (.090)	.256 (.116)	.290 (.069)
Miscellaneous	-.229 (.155)	-.049 (.764)	.091 (.633)	.103 (.526)	.152 (.355)	-.087 (.598)	.036 (.069)

Table 5. Correlation between SMT Rates and Academic Performance Measures[5]

Without an ocular measurement system to record eye movement we were unable to determine how long each active window is actually viewed after it receives focus. The *WDP* measures the maximum possible time a student could spend viewing their active windows, not the actual time. At one extreme a student might not even look at a new active window having moved their attention elsewhere before the new active window received the focus. At the other extreme, a student might give the new active window their undivided attention until the next active window is generated.

Table 6 presents a descriptive analysis of student WDP values for all multitasking categories. The overall mean was 77.9 seconds per window. On average, students spent a little over a minute with a particular software window in focus and potentially receiving attention. Each productive window was active for 120.7 seconds before a new active window was generated, while each distractive window was active for 52.5 seconds.

Table 7 presents the Pearson correlation coefficients between student WDP and academic performance measures at the .05 level for each of the software use categories. We found *very limited* support for hypothesis (2): students spending a long time viewing active windows will exhibit lower academic performance than students with a short duration times. Only the productive category showed a statistically significant inverse relationship between WDP and student performance in quiz average, project, test #2, final exam, and final course average. Neither the overall, nor any of the distractive categories showed any statistically significant relationships between WDP and student academic measures. Given that the duration of distraction has been shown to reduce productivity in the literature (Rubenstein, Meyer, and Evans, 2001), these results suggest that WDP might not be a good surrogate measure for actual window viewing duration. We also observed that the productive category had WDPs almost twice as long as any of the other categories. Perhaps there is some sort of threshold duration effect and only the productive category windows had WDPs long enough to impact student academic measures. This warrants further investigation in future studies.

Multitasking Category	Mean WDP	Std. Error WDP	Min WDP	Max WDP
Overall	77.9	5.9	21.0	166.8
Productive	120.7	10.2	24.0	268.8
Distractive	52.5	5.7	1.2	155.4
Surfing & Entertainment	70.7	9.7	0.0	273.0
Email	52.3	10.3	1.8	355.8
IM	26.7	11.9	.6	285.6
PC Operations	57.9	8.4	.6	268.2
Miscellaneous	72.8	19.0	0	652.2

Table 6. Analysis of Student WDP by Software Multitasking Category (in seconds)

5.3. The Extent of Productive versus Distractive Multitasking

For each student, we measure the ratio of distractive multitasking versus productive multitasking by dividing the student's total number of distractive windows generated by the total number of productive windows generated during the semester lectures. We introduce the student Distractive Software (DS) ratio in (3).

$$DS\ Ratio = \frac{Num\ of\ Distractive\ Windows}{Num\ of\ Productive\ Windows} \quad (3)$$

Multitasking Category	Academic Performance Measures						
	HW Ave.	Quiz Ave.	Project	Test #1	Test #2	Final Exam	Final Course Ave.
Overall	-.126 (.437)	-.105 (.520)	.122 (.519)	.036 (.826)	-.110 (.505)	-.016 (.925)	-.020 (.901)
Productive	-.241 (.134)	**-.414** (.008)**	**-.373* (.042)**	-.214 (.186)	**-.410** (.010)**	**-.431** (.006)**	**-.379* (.016)**
Distractive	-.178 (.273)	-.018 (.912)	.230 .222	.099 (.543)	-.055 (.741)	.051 (.759)	.117 (.472)
Surfing & Entertainment	-.114 (.509)	-.036 (.841)	.127 (.512)	.080 (.641)	.031 (.857)	.052 (.764)	.063 (.713)
Email	-.272 (.109)	-.014 (.936)	.132 (.493)	.294 (.082)	-.066 (.703)	-.092 (.594)	.004 (.984)
IM	-.113 (.590)	-.033 (.875)	.115 (.610)	.004 (.987)	-.060 (.775)	.101 (.631)	.022 (.915)
PC Operations	-.132 (.415)	-.144 (.376)	.037 (.846)	-.058 (.723)	-.189 (.248)	-.079 (.631)	-.026 (.866)
Miscellaneous	-.085 (.617)	.113 (.504)	.256 (.173)	.149 (.377)	.025 (.883)	.072 (.677)	.147 (.386)

Table 7. Correlation between Student WDP and Academic Course Performance Measures[5]

The DS ratio measures the mix of distractive and productive windows generated by each student during the lectures and has the following characteristics. A ratio equal to 1 means a student generated the same number of distractive and productive windows. A DS ratio greater than 0 but less than 1 means a student generated fewer distractive windows than productive windows. A DS ratio greater than 1 means the number of distractive windows exceeded the number of productive windows. Separate DS ratios were calculated for the five distractive use subcategories.

Table 8 provides a descriptive analysis of the student distractive software ratios. As a whole, students generated about twice (2.08) as many distractive windows as productive windows on average. The maximum student DS ratio observed was the generation of about seven (7.08) distractive windows for every productive window on the average. On the other extreme, the minimum student DS ratio was .26 distractive windows generated per productive window. For every 100 productive windows generated students also generated 33 surfing and entertainment windows, 27 Email windows, 43 instant messaging windows, 87 PC operations windows and 19 miscellaneous windows on average.

Table 9 presents the Pearson correlation coefficients between the student DS ratios and academic performance. We find a statistically significant negative correlation between six of the seven academic performance measures and the *distractive DS ratio*. These results support hypothesis (3): students with a greater extent of distractive multitasking compared to productive multitasking exhibit lower academic performance.

Students who generated fewer distractive windows per productive window had higher homework, quiz, project, test 2, comprehensive final exam, and final course average. Test 1 scores had a negative correlation coefficient (-.246), but it was not significant at the .05 level.

Multitasking Category	Mean DS Ratio	DS Ratio Std. Error	Min DS Ratio	Max DS Ratio
Distractive	2.08	.24	.26	7.08
Surfing & Entertainment	.33	.07	.00	2.44
Email	.27	.05	.00	1.54
IM	.43	.14	.00	3.33
PC Operations	.87	.07	.13	2.08
Miscellaneous	.19	.04	.00	1.40

Table 8. Analysis of Student DS Ratios by Software Multitasking Category

IM was the lone distractive software multitasking subcategory with a statistically significant inverse relationship between academic performance and the DS ratio. Students who generated more IM windows per productive window had lower homework averages, quiz averages, project scores, test 2 scores, final comprehensive exam scores, and final course averages at the .05 level.

5.4 Student Self-Reported Use of Email and Instant Messaging

We were able to compare self-reported email and IM use to actual email and IM use data collected via Activity Monitor™. Both email and IM laptop use during the lecture were understated / under reported by the students. Approximately 87% of students reported using email during class lectures, while 94% were actually recorded using email during the lecture. More notably, 25% of students reported using IM during class lectures, while 61% were actually observed by the spyware using IM during lectures. Email use

Multitasking Category	Academic Performance Measures						
	HW Ave.	Quiz Ave.	Project	Test #1	Test #2	Final Exam	Final Course Ave.
Distractive	**-.378* (.016)**	**-.371* (.018)**	**-.439* (.015)**	-.246 (.126)	**-.480** (.002)**	**-.455** (.004)**	**-.362* (.022)**
Surfing/ Entertainment	-.147 (.365)	-.040 (.806)	-.016 (.935)	-.089 (.548)	-.131 (.427)	-.126 (.443)	-.037 (.821)
Email	-.089 (.584)	-.148 (.362)	-.041 (.828)	-.151 (.353)	-.237 (.146)	-.078 (.638)	-.112 (.492)
IM	**-.427** (.006)**	**-.480** (.002)**	**-.683** (.000)**	-.309 (.052)	**-.540** (.000)**	**-.522** (.001)**	**-.472** (.002)**
PC Operations	-.134 (.409)	-.153 (.345)	-.192 (.309)	-.074 (.649)	-.282 (.082)	-.273 (.092)	-.184 (.245)
Miscellaneous	-.258 (.107)	-.116 (.474)	.065 (.735)	.035 (.831)	-.077 (.640)	-.201 (.220)	-.077 (.638)

Table 9. Correlation between DS Ratio and Academic Course Performance Measures[5]

was under reported by 7% while IM use was under reported by 40%.

6. SUMMARY AND DISCUSSION

The average student engages in frequent multitasking during class, generating more than 65 new active windows per lecture with 62% of those windows being classified as distractive. There is, however, limited and mixed support for the hypothesis that a higher frequency of multitasking is correlated with lower academic performance levels. At the 05 significance level, IM is the only multitasking subcategory with SMT rates that are negatively correlated with quiz average, project, and final exam grades. The PC operations multitasking category is just positively correlated with quiz average. One possible explanation for the results is that students who multitask frequently during the lecture lessen the negative performance impact by studying outside of class. If this does occur, investigating a direct causal relationship between the frequency of multitasking and academic performance requires an in-class assessment at the end of the class period and comparing those scores to the frequency of multitasking observed during that particular class.

Distractive software windows tend to have the focus for long periods of time ranging from a mean of 70.8 seconds per surfing and entertainment window to a mean of 26.7 seconds per instant messaging window. Although we are not able to explicitly measure the amount of student attention given to the active windows, the mean WDP for each distractive multitasking category is large enough to provide many opportunities for students to be seriously distracted from learning the lecture material. Also, it appears there may be no such thing as "good" (i.e. productive) multitasking when it comes to window duration times, as productive WDPs are significantly and inversely related to all performance measures except homework average and Test 1.

The fact that we do not find any significant correlations between WDPs and student performance for any of the other multitasking categories suggests that WDP may not be a good surrogate measure of the actual amount of student attention diverted from primary lecture tasks by active windows. Misleading WDP measurements could happen under certain conditions. For example, students may choose to pay little or no attention to an active window they have requested because their attention was diverted elsewhere before their request has been satisfied. The WDP measure would then overestimate the actual multitasking duration. In another example, if two different windows are entirely visible on the screen (i.e. not overlapping) at the same time, only one window can have the focus, but the student could visually move their attention from one screen to another without changing the focus. Under these conditions, the spyware would overstate the WDP measure for one window and understate it for the other.

Statistically significant inverse relationships between academic performance and both the distractive DS ratio and the IM ratio are identified. Students with higher distractive DS ratios have lower levels of academic performance as measured by homework, in-class quiz, project, exam, and final grade scores. These results show that students who allocate more cognitive resources to generating distractive rather than productive software windows exhibit lower academic performance. Students with higher IM *DS ratios* also have lower levels of academic performance in six of the seven academic performance measures. We expected similar statistically significant correlation coefficients for the surfing and entertainment, Email, and PC operations distractive software categories, but do not observe them. It is interesting to note that the IM active window category has the smallest mean window duration at 26.7 seconds per window. Although students do not keep IM windows in focus very long, the use of IM during class has a significant and substantial negative correlation with academic performance. These results suggest that compared to the other types of distractive software examined in this study, IM seems especially virulent with respect to distracting students.

We find that students under report the frequency of distractive software usage activities for both email and IM. The percentage of students using email is under reported by 7% while IM use is under reported by 40%. It is possible that student reported use may reflect social expectations rather than actual use. If true, these reporting biases would seem to pose a major problem for technology usage studies that rely solely on student perception surveys.

7. LIMITATIONS AND FUTURE DIRECTIONS

This is an exploratory study with a small sample size (90 for self-reporting questionnaire and 41 for spyware monitoring) for a single course. A larger sample size may provide the power to find additional statistically significant results and investigate causality through more complex analyses involving multivariate models of the relationship between software use and academic performance. Such studies could possibly determine the mechanism of "how" software multitasking negatively impacts academic performance. Additional research is needed to identify causal links between technology use and performance to provide the knowledge necessary to develop new technologies and learning strategies that minimize the negative impacts of software multitasking while maximizing the positive impacts.

The experimental test bed course for this study is a traditional lecture style class with content that includes both declarative and process knowledge. A significant portion of the class learning outcomes include creating cognitively complex data flow diagrams and entity relationship diagrams. Courses with a different mix of declarative and process knowledge might have different results. For example, we suspect courses with more declarative knowledge content might encourage more distractive software multitasking during the lecture while courses with more process knowledge content might encourage less. Students taking courses where a large portion of the course material is contained in a textbook and academic performance is measured largely through recognition and recall could have a higher frequency of distractive multitasking behavior during class lectures.

The test bed course requires the use of laptops and there are many class periods where software use is a critical component of the primary learning task. The findings of this study might differ for courses that do not require laptop use during the lecture because there may be relatively few productive uses of laptops in those courses. Classes that allow laptop use during the lecture but do not actively require their use to learn the course material are likely to have different multitasking and usage trends. The affects of using laptops in these classes may also be different.

While we test for a self-selection bias based on the past performance of students and discuss issues regarding student laptop usage and whether or not their behaviors change given that the students know they are being monitored, it is important to acknowledge the potential impact of the Hawthorne effect. It is possible that some of the students who participated in the study using Activity Monitor™ altered their behavior in some way given that they knew they were being monitored. We did fine plenty of anecdotal evidence involving inappropriate messages about classmates and / or the instructors suggesting that at least some students didn't seem to feel constrained at all by the fact that they were being monitored. It appears that any bias that might occur would tend to underreport distractive or inappropriate behavior. Therefore, the study results could be considered conservative with respect to the frequency, duration, and extent of distractive multitasking.

Another issue that warrants future study is investigating how laptops might be used to maximize learning while at the same time minimizing distraction. Obviously, part of the responsibility for facilitating non-distracting laptop use lies with the educator and part lies with the student. Both students and educators can benefit from better information regarding the potentially negative impacts arising from distractive laptop use. Students may need guidance on how to minimize distracting laptop usage, while educators may need to be more involved with encouraging / discouraging certain types of behaviors in the classroom. Additional studies that address how differences in course structure, content, and evaluation methods might facilitate more positive learning outcomes with respect to laptop usage in the classroom are needed.

It appears that more students are bringing new and sophisticated technologies to the lecture with advanced multitasking skills to match. However, students may not fully understand the potential negative impacts created by recreational multitasking use. Perhaps a better approach to banning laptops from the classroom is to encourage additional research into better ways to measure multitasking laptop use in the classroom to identify new empirically tested learning strategies.

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9. ENDNOTES

[1] Most studies rely on self-reported perceptions of use or anecdotal descriptions of use.
[2] This project obtained approval to conduct this research from the University's Committee on Human Research and study participants completed an approved consent form.
[3] ACE is a measure used by UVM Admissions to review and rank prospective student applicants. There are three components to the ACE: 1) high school graduating class rank, 2) SAT or ACT score, and 3) the strength of the high school based on the percentage of college bound graduating seniors. Each prospective student is assigned an ACE with values ranging between 1 and 9.
[4] This relates directly to the Hawthorne effect; a reaction by subjects that involves changing or improving certain aspects of their behavior in response to the fact that they are being studied and not in response to experimental manipulation. In this case, we were concerned that students might not engage in certain behaviors using their laptops because they know that they are being monitored. We test for a self-selection bias (Table 3) and examine anecdotal evidence that suggests this type of bias did not overtly impact the study results.

[5] For this table the correlation coefficient is the top value, followed by the 2-tailed *p*-value in parentheses. Bold values with a single asterisk identifies values significant at the 0.05 level while bold values with two asterisks denotes significance at the 0.01 level

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