Student Attention in Unstructured-Use, Computer-Infused Classrooms

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1. Introduction

The number of computer-infused classrooms is growing due to an increasing number of engineering programs requiring students to purchase personal computers[1]. As classroom instructors, we have stood before the sea of computers and wondered, "*How many students are taking notes?*" "*How many students are playing on Facebook?*", and, ultimately, "*Are laptops aiding or hindering student learning?*". We are not alone in our questions. As evident from numerous research studies (e.g., [2-7]) investigating the use of personal computers in the classroom, the potential for computers to be a distraction from learning is a common concern.

Unfortunately, current research studies have resulted in a dichotomy with some studies concluding personal computers reduce academic achievement (e.g., [4, 6]) and other studies concluding personal computers have positive learning effects (e.g., [8, 9]). Focusing on identifying pedagogical practices and classroom factors that maximize the benefits of computers and those that minimize the distractions is one suggested solution[6, 7]. However, current data collection methods are inadequate or inappropriate for capturing student computer use data that could be connected to classroom activities.

This purpose of the research presented in this paper is to investigate the potential of a simplified electronic monitoring tool to quantify student attention throughout a class period. The simplified electronic monitoring tool solely reports a binary determination of attention, "on-task" or "off-task", which is based on students' top-most, active window, "course software" or "not course software". Thus, the primary question driving this study is:

How can binary attention data inform our understanding of student attention and instructional design?

We discuss insights obtained through our initial exploration of binary attention data. We foresee that this simplified method could be correlated with instructional methods and classroom activities in order to more thoroughly investigate the overarching research question: *How do students use laptops in a technology-infused classroom?*

2. Background

2.1. Computers in the Classroom: Unstructured- and Structured-Use

Generally, there are two types of computer-infused classrooms, structured-use and unstructured-use[7]. In the structured-use paradigm, computers are integrated into instructional activities in a meaningful and deliberate manner and every student is required to bring a computer to class. In the unstructured-use paradigm, instructors may use computers for lecture delivery, but student computer use is neither directed nor required.

Clear examples of unstructured use exist in the literature. In one example of unstructured use, Connor[2] focused on students within a College of Engineering with a personal computer requirement. The class was a traditional lecture format and students were allowed to bring computers to class. There is no indication that the instructor directed or guided student computer use, nor was there indication that lecture slides were made available to students. This type of lecture classroom is often described as the "traditional" lecture format.

Clear examples of structured use also exist in the literature. In one example of structured use Lohani et al.[8] describe how they fully integrated Tablet PC (TPC) computers into lecture for note taking, collaboration, and problem solving purposes. Students' computer use was directed by instruction on how to use their computers productively with various software packages (e.g., OneNote) and through short activities during lecture.

However, there also exist several examples of classrooms that are not clearly structured or unstructured. For example, in Hembrooke and Gay's study[5] instructors provided URLs during lecture and encouraged students to elaborate on lecture content during lecture. Although this activity fits the definition of structure use since the instructors directed students' computers use, ultimately, the results indicated that some students would disengage and participate in unstructured use. This type of directed computer use had a negative effect on learning. In another unclear example, Samson[9] reported on a classroom in which the chat feature of interactive learning software was used to increase interaction with students in a large lecture. Since there was not a computer requirement at the study site, there was no requirement that students bring computers to class, but majority did. While students reported increased off-task activities, they also indicated using the chat feature increased engagement. This was supported by the instructor's observation of an increase in the number of questions posed from students.

In past research, the structured-use paradigm has been related to increased student attitudes and successful behaviors that support learning. Despite this finding, the unstructured-use continues to be the predominate configuration in classrooms because of the time requirements for instructors to learn instructional technology and the time requirements for modifying lectures[10, 11].

2.2. Importance of Attention for Learning

One possible explanation for the difference in learning between structured-use and unstructured-use computer-infused classrooms is that structured-use encourages student attentiveness. Distraction and inattentiveness are significant concerns for educators as attention is a fundamental requirement for learning. Understanding students' in-class computer usage and its impact on their attention is crucial since attention is a critical element of the learning process. Robert Gagne's Conditions of Learning Theory[12, 13] stipulates that there are nine instructional events that must occur for learning to take place, the first of which involves obtaining the learner's attention. The instructional events, shown in Figure 1, do not guarantee learning will occur, but rather they support the learner's internal mental processes. That is, each event is a necessary condition for learning to take place. Fleming[14] put it best: "Quite simply, without attention [the first event] there can be no learning" (p. 236). Fleming goes on to propose that course designers have control over attention, and recommend that they "seek both to obtain the learner's attention and to keep it." (p. 236).

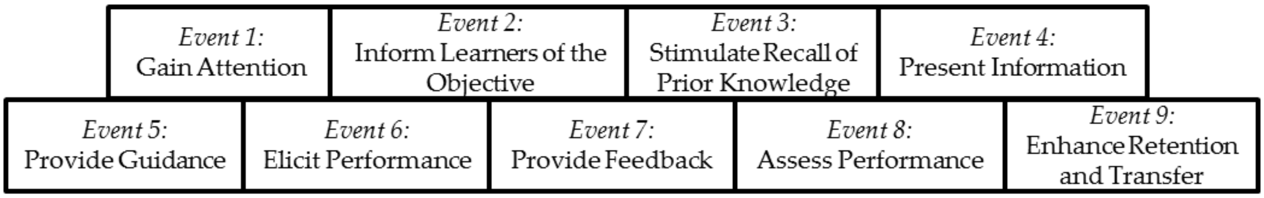


Figure 1. Robert Gagne's[12] Conditions of Learning Nine Instructional Events

2.3. Current Data Collection Methods Issues

The majority of existing research on personal computers has relied heavily on survey data in order to determine how much non-academic computer use occurs in the classroom. A critical limitation of survey studies is that self-reported data can be unreliable. Specifically, threats to reliability of self-reported data include: i) students' memory or perceptions may not match reality, ii) students may report inaccurate results if they perceive a threat (e.g., a threat to their grades), and iii) not all students respond.

For example, Doolen, Porter, and Hoag[3] administered their survey at the end of the semester, which required students to recall their computer usage throughout the entire semester. Students may be unable to accurately recall their computer use from early in the semester. Even if recall is accurate, since students are grade-oriented[18], they are likely to be focused on their final grade at the end of the semester and unlikely to report negative behavior such as inappropriate computer use.

Low response rates have also been documented (e.g., in Lauricella and Kay's study[19], the response rate was 34%). Other studies have achieved much higher response rates at the end of the semester mainly by offering extra credit to grade-focused students during the last week of class (e.g., Kraushaar and Novak's response rate was 93%[6]). Higher response rates in that situation are not surprising, but the effect on data validity and reliability remains unclear as students also underreported their non-academic usage in both studies.

To avoid issues with self-reported and observational data, some researchers have looked towards electronic monitoring of students' computer use. For example, Hembroke and Gay[5] used web usage data obtained from a proxy server. While their study produced useful results, the reliance exclusively on Internet data produced an incomplete characterization of student computer use. Their characterization neglected to include students who may be playing off-line games, editing documents, and performing other tasks that do not require the Internet.

Kraushaar and Novak[6] collected more comprehensive data by installing spyware on students' computers that recorded active window information (e.g., program name, window duration period) and keystrokes. The authors compared the spyware data with survey results to determine the degree that students underreport in-class computer use on surveys. Additionally, Kraushaar and Novak used the spyware data to examine the effects of multitasking on academic performance. Both studies were exploratory studies with small sample sizes; widespread deployment of spyware as a data collection method is impractical due to privacy and ethical concerns, and conflicts between spyware and antivirus software.

3. Methods

3.1. Context

The study was conducted at a large research university located in the Southeast United States. The university's College of Engineering (CoE) has an established Tablet PC (TPC) requirement. Compliance with the requirement is near 95% resulting in numerous personal computers in classrooms. The CoE supports interactive learning software primarily to distribute course content (e.g., slides) to students. In addition, the software can be used to implement various instruction interventions including polls, electronic ink, and screen broadcast[15]. The current software and version is DyKnow Vision 5.5.

At our study site, there are three general classroom classifications based on instructor and student computer use:

1. **Unstructured** – e.g. the instructor uses the chalkboard and students are free to bring their computer to class
2. **Unstructured with DyKnow** – e.g., the instructor uses DyKnow Vision to distribute instructor-generated slides and notes to students who use their computers to capture content and/or for note-taking
3. **Structured** – e.g., the instructor uses DyKnow to distribute instructor-generated content and directs student computer use with polls and active learning activities

In "Unstructured" and "Unstructured with DyKnow" courses, students are not required to bring computers to class. In "Structured" courses, students are required to bring their computers because the active exercises are integral components of the lecture. In this paper, we report findings from our initial research investigation in an "Unstructured with DyKnow" statics course.

3.2. Participants

The course selected for this study was a Statics course that was purposefully chosen based on the instructor's familiarity with and use of DyKnow Vision. In the Fall 2012 semester, the instructor taught one section of Statics (~250 seats) in a large auditorium with stadium style seating. The course met on Tuesdays and Thursdays for one hour and 15 minutes. The selected instructor used a Tablet PC to distribute slides and lecture notes to students via DyKnow. Lecture notes were also projected in the front of the classroom. The lecture usually began with a review of student selected homework problems, was followed by a short lecture covering new concepts, and concluded with example problems. The instructor would use the class roster to create an interactive environment by randomly calling on students to assist him when working problems.

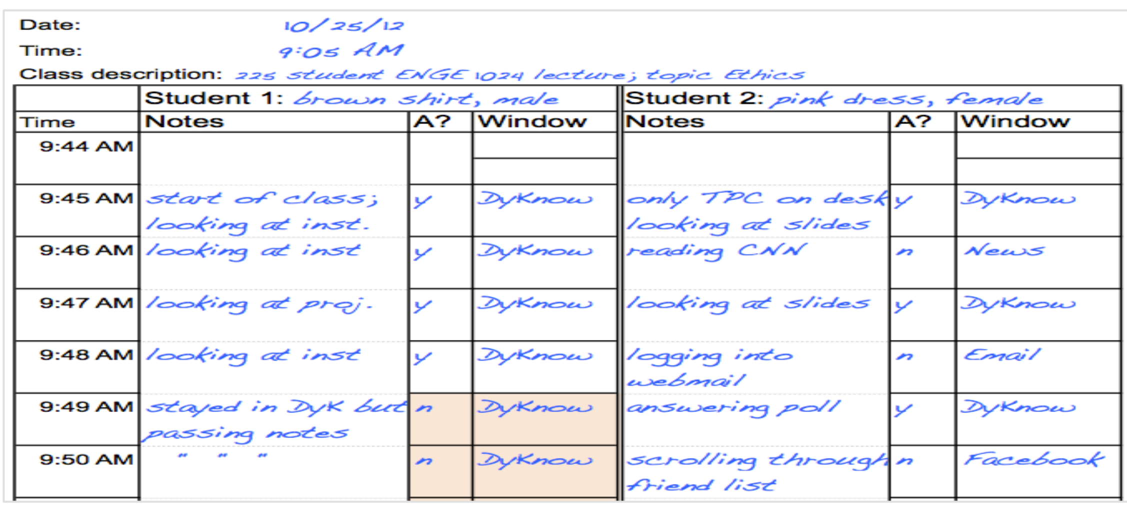
All Statics students have completed the CoE first-year program, in which DyKnow is used in the "Structured" format and students receive basic DyKnow software training. In the beginning of the Fall 2012, Statics students were told that they could use DyKnow to capture, annotate, and save lecture content. However, students were not required to use a computer, and lecture slides (i.e., the instructor's DyKnow file) were posted at the conclusion of each class. Since this research investigates student computer-use, only students who brought a computer to class were included in the study.

3.3. Data Collection Method: Observations of Attention

In order to avoid issues with self-reports data (e.g., underreported off-task use[6]) and to collect attention data in real-time, we conducted observations of multiple lectures from our identified Statics course section. Direct observations of student behavior are a frequent and recognized method for determining student attention in educational, behavioral, psychological research studies[16, 17]. In determining attention, observations may focus on general behaviors, such as "on-task", or specific behaviors, such as "playing with an object". Focusing on general behaviors is recommended since significant and consistent evidence exists for the validity of general measures[16].

We used in-class, naturalistic observations, which are unobtrusive, covert observations during which the observer blends in with participants and does not affect behavior. Observations were conducted during randomly selected lectures. Prior to the start of lecture, the observer would sit in a random location in the classroom, and then select two students whose computer screens were visible. Since neighboring students can distract each other[4], the selected students could not be sitting next to each other in order to ensure two separate data points.

The sample observation protocol (Figure 2) guides observers to document how students interact with and without their computers. At the start of lecture and at every minute thereafter, the observer documented any information relevant to attention (Notes), the observer's opinion of student attention (A?), and the student's top-most window (Window) on the observation protocol (Figure 2 – blue text). Generally, a student is attentive if they are looking at course content or the instructor, discussing course content, working on instructor-assigned tasks, or listening to the instructor. In other words, a student is on-task or attentive if they are participating in teacher-sanctioned activities[16].



Date: 10/25/12
Time: 9:05 AM
Class description: 225 student ENGE 1024 lecture; topic Ethics

	Student 1: brown shirt, male			Student 2: pink dress, female		
Time	Notes	A?	Window	Notes	A?	Window
9:44 AM						
9:45 AM	start of class; looking at inst.	y	DyKnow	only TPC on desk looking at slides	y	DyKnow
9:46 AM	looking at inst	y	DyKnow	reading CNN	n	News
9:47 AM	looking at proj.	y	DyKnow	looking at slides	y	DyKnow
9:48 AM	looking at inst	y	DyKnow	logging into webmail	n	Email
9:49 AM	stayed in DyK but passing notes	n	DyKnow	answering poll	y	DyKnow
9:50 AM	" " "	n	DyKnow	scrolling through friend list	n	Facebook

Figure 2. Observation protocol with sample text (blue) and highlighted mismatches (orange)

3.4. Data Collection Method: Electronic Monitoring of Attention

Our second source of data was an electronic record of student attention. DyKnow Vision 5.5 includes a widget that gives instructors a visual representation of student attention by monitoring students' active, top-most window (Figure 3). The software assumes that DyKnow application indicates a student is on-task and that all other applications indicate off-task behavior.

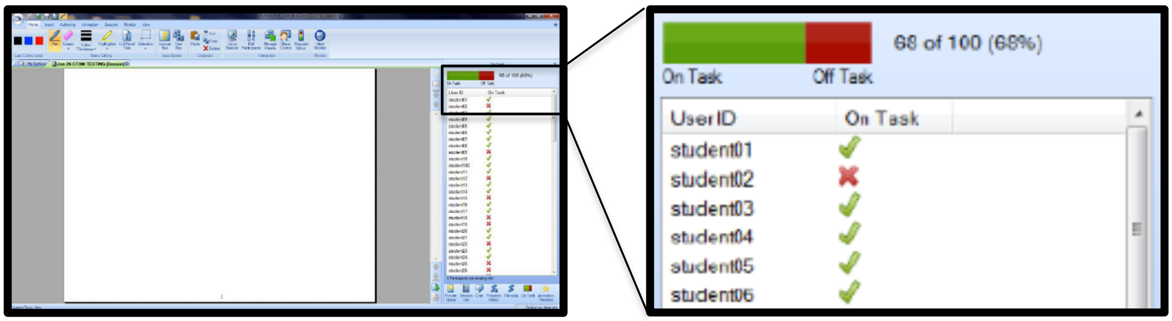


Figure 3. DyKnow Vision's on/off-task feature

We created a record of the widget's output with screen capture software. We then processed the recordings with MATLAB's image processing toolbox to create a Microsoft Excel file for analysis. In courses where students are required to use DyKnow, this electronic data collection method has the potential to capture a real-time attention record for every student, as well as the average class attention. In courses where students have the option of bringing a computer to class, such as the Statics course discussed in this paper, the tool will capture a record for every student who brings a computer to class and logs into DyKnow.

4. Results

During the Fall 2012 semester, ten observations were conducted in ten 75-minute Statics lectures. Two students were observed during each lecture, for a total of 20 observed students. One student was excluded from analysis due to shortened observations due to the student (O-03804) leaving class significantly early. Observations were conducted over eight weeks (weeks 01 – 07, and 11). Up to four students could be observed a week due to the course having two lecture meetings. For consistency in coding, even if only one observation was conducted during a given week, students observed on Tuesdays are coded 801 and 802, and students observed on Thursdays are 803 and 804, where the 8 is course code. The student identification code in Figure 4 reflects this information. For example, student O-05803 was observed (O) during the fifth week of Statics (05), and was the first student selected on a Thursday (803). The nineteen student identification codes reflect nineteen different students.

On Tuesday during week five, attention data was recorded through DyKnow. Attention records were captured from 135 students who used DyKnow Vision 5.5. Data were not captured from (a) the 63 students who used an older version of DyKnow Vision that does not send data to the on-task widget, (b) students who did not use DyKnow, and (c) students who were not present in class.

4.1. Observed Student Attention

The observation "Notes" field was analyzed to determine the characteristics of a student who is paying attention versus a student who is not paying attention. Those characteristics are listed in Table 1. The characteristics provide validity to the observer's determination of attention as they aligned with instructor expectations for attentive and non-attentive students.

Table 1. Student characteristics from the observation protocol "Notes" field

Paying Attention	Not Paying Attention
Listening to instructor	Installing software
Taking notes / writing on slide	Talking to neighbor
Participating / Answering Poll	Spacing out / Sleeping
Copying instructor's notes	Doodling (and not listening)
Asking questions	Working homework
Looking at instructor / projector	Checking email / Surfing web
Helping neighbor on assignment	Writing report
Looking at handout	Texting
Submitting a slide	Flipping through previous slides

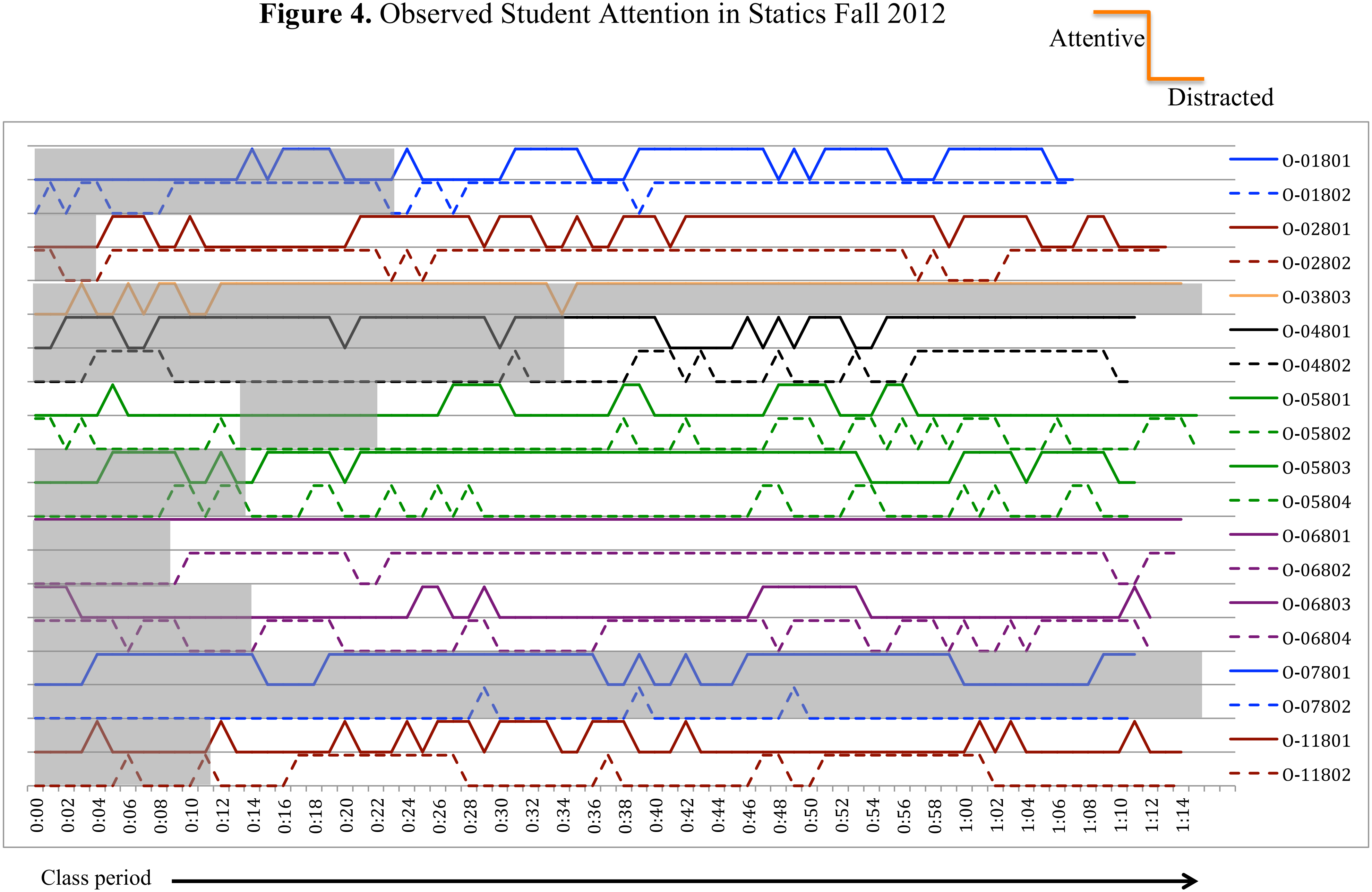
Student attention was obtained from the observation protocol column "A?" and is shown in Figure 4. The data was coded with 1s to indicate on-task (the high line) and 0s to indicate off-task (the high line). The gray shading indicates the portion of the lecture when the instructor reviewed homework. During the observation period in week three (O-03), the instructor reviewed previous material and homework during the entire lecture because he had been absent from the previous lecture. During the Tuesday observation period in week 5 (O-05), the instructor discussed the exam that was held in the previous lecture (indicated by the initial white area), then they reviewed homework (gray shading) before switching to lecture (second white area). During the observation period in week 7 (O-07), the instructor reviewed previous material and homework during the entire lecture in preparation for students' upcoming exam.

Percentage of time on-task for each student (Table 1) was calculated by dividing the number of attentive instances by the total number of observation instances. Attention levels are widely distributed with an average on-task time of 53%, a low of 4% and a high of 100%.

Table 1. Percentage time on-task for 19 observed students

Student	% On-task	Student	% On-task	Student	% On-task
O-01801	49%	O-05801	17%	O-06804	60%
O-01802	86%	O-05802	26%	O-07801	66%
O-02801	58%	O-05803	73%	O-07802	4%
O-02802	86%	O-05804	23%	O-11801	24%
O-03803	88%	O-06801	100%	O-11802	36%
O-04801	79%	O-06802	81%		
O-04802	34%	O-06803	19%		

Figure 4. Observed Student Attention in Statics Fall 2012



4.2 Electronic Monitored Student Attention

Percentage of class time spent in DyKnow was calculated for each of the 135 electronically monitored students and the frequency distribution is shown in Figure 5. The average percentage on-task time is widely distributed, with only 35 students in the 90-100% attentive category.

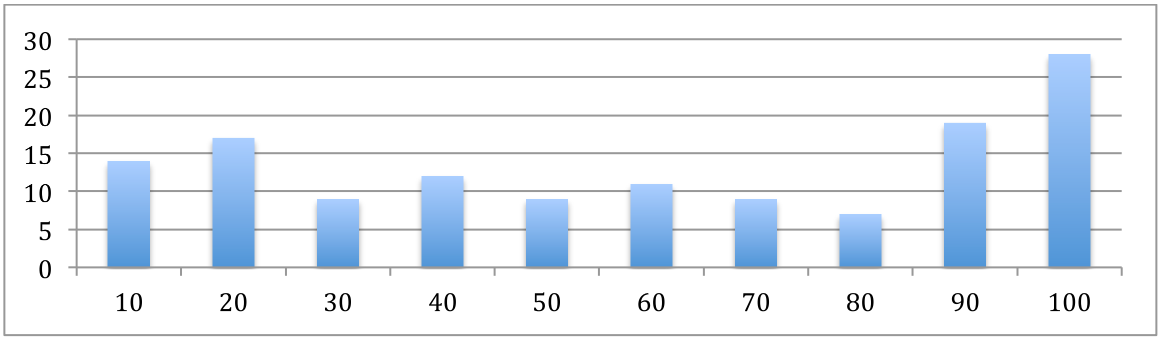


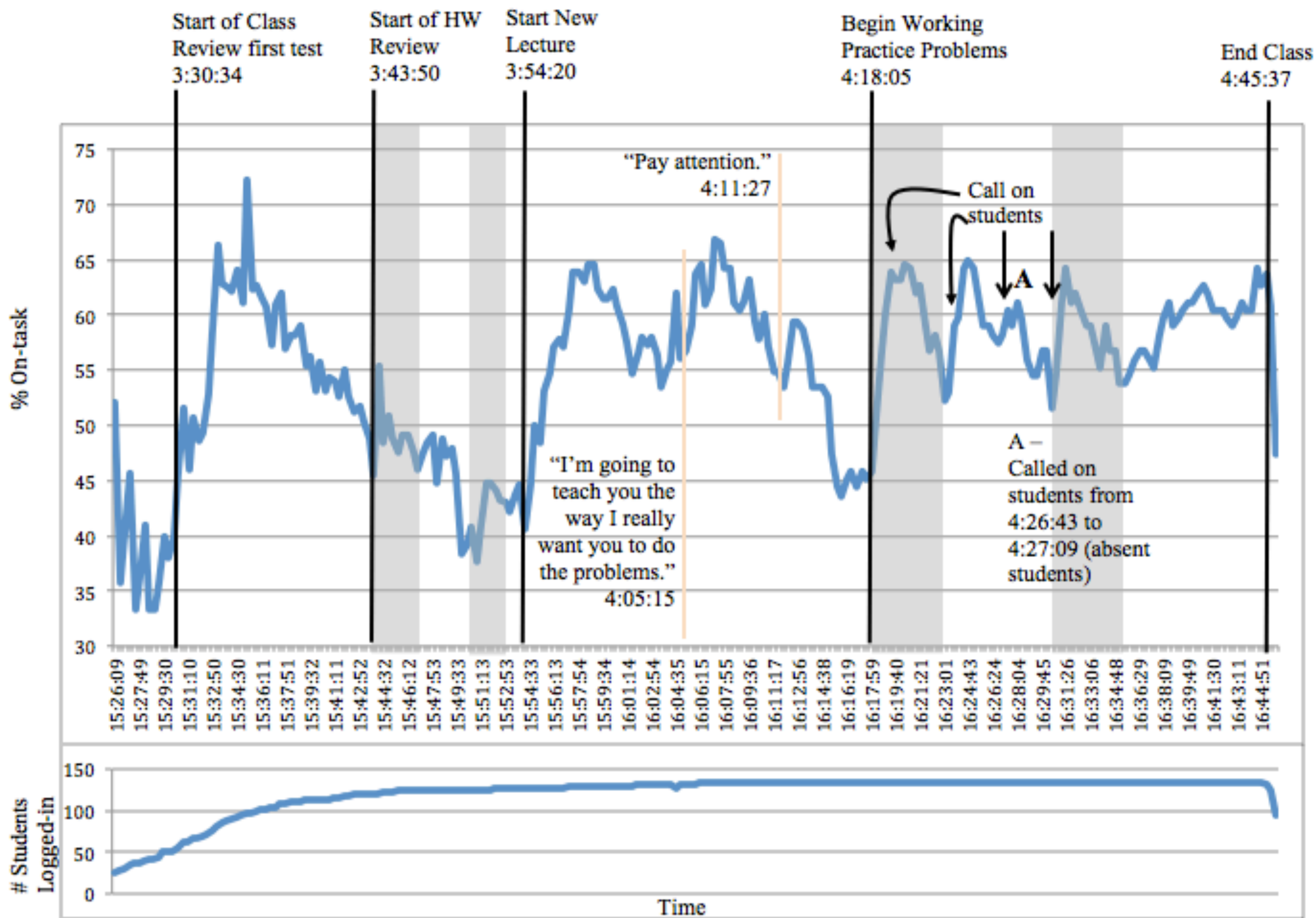
Figure 5. Frequency Distribution of Percentage On-task for 135 Students in Tuesday's Week Five Statics Lecture

Attention was measured every 12 seconds for the entire 75-minute lecture. For each time, average class attention was calculated by dividing the total number of attentive students (e.g., DyKnow as top-most, active window) by the total number of students logged into DyKnow (Equation 1). A timeline of average attention monitored through the DyKnow widget is shown in Figure 6 (next page).

$$Average\ Class\ Attention = \frac{total\ students\ with\ DyKnow\ active}{total\ students\ logged\ into\ DyKnow} * 100 \qquad (1)$$

The average class attention timeline was supplemented with information from the observation protocol, observation notes, and an audio recording of lecture in order to create a descriptive class timeline (i.e., start of class, start of homework review, start of new lecture material, start of practice problems related to new lecture material). During the homework review and practice problem sessions, gray shading is used to indicate the start and end of different problems.

Figure 6. Timeline of Week 5 Activity and Percentage of Class in Interactive Learning Software



5. Discussion

The results from this initial study support our premise that we can use students' active window to capture attention data from all students in real-time. This data has the potential to provide insights into student attention and the effects of classroom activities on students' attention and learning.

First, our initial evaluation of the binary attention data obtained from observations and presented in Figure 4 indicates that students have different modes of attention. As examples, consider participant O-01802, who remains on-task for a majority of lecture, but occasionally "checks out" of lecture. Compare participant O-01802's behavior with O-11801 who is mostly off-task, but occasionally "checks in" to lecture. We also observe various on-task and off-task duration periods. For example, participants O-02802 and O-03803 have long on-task duration periods whereas O-05801 and O-05802 have very short on-task periods. Participant O-07802 is off-task for nearly the entire lecture (on-task for only 4% of lecture), while participant O-06801 is on-task for the entire lecture. On-task duration period, amount of task switching, and overall percentage on task may combine to define distinct modes of attention.

Second, our data indicates that students pay less attention during portions of class dedicated to announcements of homework problems. As an example, participant O-06802 is off task during the homework review portion of lecture (gray area), and begins paying attention at the start of the lecture. Likewise, the start of lecture is correlated with a switch to on-task behavior for O-01802, O-02802, O-05803, and O-11801. Mindful of the small sample size for observations, we examined the class attention timeline presented in Figure 6 (N = 135) and observe decreasing attention until the start of lecture, which appears to trigger an increase in on-task behavior.

Third, by annotating the average class attention time line in Figure 6, we see a clear indication that instructors effect student attention. When new material was presented, there were peaks (e.g., local maximums) in attention. Furthermore, instructor statements such as "Pay attention" also promoted attention, but the duration was short lived. Randomly calling on students while working on practice problems may be a method of returning students to lecture, but another method must be used to prolong the increased engagement, as students would return to off-task activities when they realized that they were not selected. This empirical evidence is consistent with discussions of active learning pedagogy that indicate the delivery system and pedagogical techniques can directly affect student engagement[20, 21], and with calls challenging instructors to take responsibility for student engagement[22].

Finally, when comparing human observations of attention (Section 3.3) and electronically monitored attention data (Section 3.4) in regards to data quantity, electronic monitoring is clearly superior. A single observer was only able to capture attention timelines from two students per a lecture. The observed attention timelines were captured at 1-minute intervals. While the limits of two students at 1-minute intervals were set prior to data collection, we expected that the observer would be able to increase the number of students observed per lecture or decrease the observation interval as the observer became more familiar with the observation protocol. In general, this was not the case. In sessions where participants had long durations of on-task behavior (e.g., O-06801 and O-06802 in Figure 4), the observer reported that they might have been able to observe an additional student. However, in cases where students were engaged in a high amount of task switching (e.g., O-11801 and O-11802 in Figure 4), the observer could neither observe more students nor observe the two students at more frequent intervals. On the other hand, the electronic monitoring tool was capable of capturing data from all students using DyKnow Vision 5.5, and in our case produced 135 attention timelines for a single lecture period. The timelines were captured in near real-time, with the timing limited only be the need to scroll the visual DyKnow widget in order to capture individual student timelines. Using observation methods to collect the quantity of data collected with the electronic monitoring tool requires an army of observers.

We have presented a baseline case of attention in semi-structured course, and have demonstrated the potential of binary attention data to inform our understanding of student attention. The successes presented in our initial investigation of attention timelines encourage the expansion of this research in different courses and course types. We are currently investigating attention in additional large lectures with structured computer use. It is ultimately expected that our findings can be used as empirical evidence to encourage instructors to incorporate structured computer-use into their pedagogical practice.

5.1 Limitations

There is a need to quantify the amount of error when using active window as a proxy for attention. During observations, students were often observed listening and looking at the instructor or projected slide (i.e., "checking in"), but continued to have their browser open as the top-most, active window. Our observation protocol allows for a comparison between observed attention and active window and we plan to use that data to calculate error rate. Based on the observations in this study, we anticipate that error rate will be less than 10%. We also anticipate the error rate to be inversely proportional to the amount of direction students receive for their computer use as it appears students "check-in" at a higher frequency during long off-task sessions.

The downside to the quantity of data available through the electronic monitoring tool is that the data is less rich. Whereas the timelines generated from observations (Figure 4) have contextual data (e.g., specific on-task or off-task behaviors that students were engaged in, see Table 2), data collected through capturing the DyKnow widget solely indicates "in course software" or "not in course software". Lack of context for the electronically monitored data may reduce the usefulness of electronically monitored data.

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