

ASSESSMENT OF ENGAGEMENT FOR INTELLIGENT EDUCATIONAL AGENTS: A PILOT STUDY WITH MIDDLE SCHOOL STUDENTS

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Abstract

Adaptive learning is an educational method that utilizes computers as an interactive teaching device. Intelligent tutoring systems, or educational agents, use adaptive learning techniques to adapt to each student's needs and learning styles in order to individualize learning. Effective educational agents should accomplish two essential goals during the learning process – 1) monitor engagement of the student during the interaction and 2) apply behavioral strategies to maintain the student's attention when engagement decreases. In this paper, we focus on the first objective of monitoring student engagement. Most educational agents do not monitor engagement explicitly, but rather assume engagement and adapt their interaction based on the student's responses to questions and tasks. A few advanced methods have begun to incorporate models of engagement through vision-based algorithms that assess behavioral cues such as eye gaze, head pose, gestures, and facial expressions. Unfortunately, these methods typically require a heavy computation load, memory/storage constraints, and high power consumption. In addition, these behavioral cues do not correlate well with achievement of high-level cognitive tasks. As an alternative, our proposed model of engagement uses physical events, such as keyboard and mouse events. This approach requires fewer resources and lower power consumption, which is also ideally suited for mobile educational agents such as handheld tablets and robotic platforms.

In this paper, we discuss our engagement model which uses techniques that determine behavioral user state and correlate these findings to mouse and keyboard events. In particular, we observe three event processes: total time

required to answer a question; accuracy of responses; and proper function executions. We evaluate the correctness of our model based on an investigation involving a middle-school after-school program in which a 15-question math exam that varies in cognitive difficulty is used for assessment. Eye gaze and head pose techniques are referenced for the baseline metric of engagement. We conclude the investigation with a survey to gather the subject's perspective of their mental state after the exam.

We found that our model of engagement is comparable to the eye gaze and head pose techniques for low-level cognitive tasks. When high-level cognitive thinking is required, our model is more accurate than the eye gaze and head pose techniques due to the students' non-focused gazes during questions requiring deep thought or use of outside variables for assistance such as their fingers to count. The large time delay associated with the lack of eye contact between the student and the computer screen causes the aforementioned algorithms to incorrectly declare the subjects as being disengaged. Furthermore, speed and validity of responses can help to determine how well the student understands the material, and this is confirmed through the survey responses and video observations. This information will be used later to integrate instructional scaffolding and adaptation with the educational agent.

Introduction

The purpose of this paper is to discuss a reliable, noninvasive method of monitoring academic engagement within the domain of computer-based education (CBE). In successful classroom settings, teachers are able to observe a student's engagement in real-time and employ strategies to reengage the student, which, in

effect, improves attention, involvement and motivation to learn [1]. This is also true during one-on-one tutoring sessions due to the fact that tutors are able to track engagement in real-time as well. In general, teachers are able to determine engagement by following behavioral cues from students such as direction of attention, posture, facial expressions, and responsiveness to instructional activity [2]. This behavioral engagement is a crucial component in education because it is often related to the academic achievement of a student [3,4].

Currently, educational software is a widely used method of instruction inside the classroom and at home. Research has shown that CBE actually improves academic achievement [5] and student motivation [6] when compared to traditional classroom instruction. Using CBE reduces the amount of instructional time required and increases the student's attitude towards learning [7]. Although research has shown CBE as being a highly effective learning tool, it pales in comparison to a human tutor [5]. Therefore, CBE should be used as a supplement to traditional instruction and not as a replacement [8]. In this investigation, we will determine how a computer-based system can monitor student engagement in a manner comparable to that of real classroom teachers.

Related Work

CBE primarily focuses on comprehension of material [9] and not real-time engagement, which is essential for optimal academic achievement. In computer-based education, comprehension of material is determined solely by the validity of answer selections. Many standardized tests today, such as the SAT and GRE, adapt to the students based exclusively on their responses. This type of evaluation is known as computerized adaptive testing (CAT) [10]. If the student answers a question correctly, he/she is given a more difficult problem. If the student answers a question incorrectly, he/she is given a problem of less difficulty. However, for an educational system to be optimum, it must ensure that the student is actively and

continuously engaged. Computer-based tools only focus on comprehension because of the difficulty associated with determining cognitive states. Due to the variability of behavior, characteristics, and environment, computer-based educational tools with the capability of identifying the behavioral cues associated with engagement have yet to be developed [1].

As an alternative to measuring engagement in real time, scales have been created to evaluate motivation once the student has completed a system [11]. The problem with this method is that an educational agent will not be able to adapt to the educational needs of the student once the learning session is complete. The art of adaptation requires real-time information processing, which scales are unable to deliver.

A more promising alternative to measuring engagement is through electroencephalography (EEG) signal measurements. EEG signals are able to identify subtle shifts in alertness, attention, and workload in real time [12]. Szafir and Mutlu used an EEG headset to monitor engagement in an educational setting through storytelling [1]. When the EEG signals would begin to drop during narration, adaptive behavioral cues (verbal and non-verbal) would be used to re-engage the students. EEG measurements have the advantage of being minimally-invasive, well studied, and low cost [1]; however, wearing a headset creates a controlled testing setup, which does not convey a natural learning environment. This ultimately has the potential to cause unnecessary distractions and distort results.

In efforts to create a non-invasive tool to monitor engagement in real time and within a natural learning environment, a viable option would be to use eye gaze and head pose to determine behavioral user state. Asteriadis et al. was able to develop a system using head pose and movement, direction of gaze, as well as measurements of hand gesture expressivity to determine six user states in an e-learning environment: attentive, full of interest, frustrated/struggling to read, distracted,

tired/sleepy, and not paying attention [13]. The developed system was able to effectively detect reading- and attention-related user states very well when subjects were asked to read/watch an electronic document (web page, multimedia presentation, video clip). However, this system was not tested in a complex problem solving or test-taking environment.

Engagement Metrics

In this paper, we discuss a novel model of student engagement based solely on mouse and keyboard events that leverages previous eye gaze and head pose research. Events are composed of mouse left/right clicks and keystrokes. Three event processes are observed to identify a common pattern associated with both an engaged and disengaged student: total time, response accuracy, and proper event execution. This data is collected as the students take a 15-question math test.

Before the proposed engagement model can be utilized by an educational agent, a pilot test is needed to determine a baseline for performance, i.e. the level of difficulty and appropriate amount of time needed to complete each question. If the test/questions are later modified, new time distributions will need to be calculated for evaluating the student's engagement level using the model. In this investigation, we 1) validate that determining engagement is possible with solely event processes and 2) develop the aforementioned performance metrics for each question. In [14]-[17] we take this a step further by deriving the engagement model using this data and applying it to an intelligent educational agent to provide real-time feedback to the student.

Total Time

The difficulty of a problem is determined by how much time is needed to submit a well thought out answer. Difficulty is directly proportional to the amount of time needed to respond. However, this exact allotment of time per question is unknown due to the subjectivity

of classifying the difficulty level of problems. Therefore, in this investigation we used a distribution of the time taken by a pilot group of students to determine the ideal time needed to adequately answer a particular problem. The ideal response time falls within the interquartile range (IQR) of the data. If a student answers within the lower quartile, his/her response is classified as fast. If a student answers within the upper quartile, his/her response is classified as slow. If a student answers within the IQR, his/her response is classified as average.

Next, we calculate the total amount of time needed to complete the entire 15-question math test. This ideal test time is determined by a distribution of the time taken by a pilot group of students to adequately complete the test. The ideal test time will fall within the IQR of the data. If a student answers within the lower quartile, his/her test time is classified as fast. If a student answers within the upper quartile, his/her test time is classified as slow. If a student answers within the IQR, his/her test time is classified as average.

Response Accuracy

Response accuracy is defined as the correctness of the submitted answer. As mentioned previously, this technique is currently widely used with standardized CAT. If a student answers a question incorrectly, his/her accuracy is classified as incorrect. If a student answers a question correctly, his/her response will be classified as correct.

Proper Function Execution

Initially, we identify a set of functions and event(s) as shown in Table 1. The functions are a list of all the possible options (identified as buttons on the test interface) that can be used to effectively navigate through and complete the math test (begin test, next question, previous question). Next, the corresponding keystrokes and mouse click locations are listed for each function. The equations for the location of the mouse clicks is specific to the platform used for

implementing the test; as long as the platform is the same, the test/questions can change and the derived equations will still hold true.

If a key or combination of keys is used that falls within the list of needed keys to execute a function, the student is classified as being on-task. However, if a key or combination of keys is used that falls outside of the list of needed keys to execute a function, the student is classified as being off-task. Similarly, if the mouse is clicked at a location that falls within the list of needed clicks to execute a function, the student is classified as being on-task. However if the mouse is clicked at a location that falls outside of the list of needed clicks to execute a function, the student will be classified as being off-task. In Table 1, only *left* mouse clicks are mentioned since right clicks cannot be used to select options in the test interface. One can assume that if a right click occurs, the student either clicked it by accident or is off-task.

Table 1: Functions and Events.

Functions	Keystroke	Mouse Left Click Location
Begin	n/a	$(x - 686)^2 + (y - 654)^2 \leq 74^2$
Next	n/a	$(x - 1125)^2 + (y - 680)^2 \leq 42^2$
Previous	n/a	$(x - 245)^2 + (y - 676)^2 \leq 43^2$
Select A	A	$x: 199 - 424; y: 474 - 626$
Select B	B	$x: 448 - 673; y: 474 - 626$
Select C	C	$x: 696 - 921; y: 474 - 626$
Select D	D	$x: 945 - 1170; y: 474 - 626$

Because the student may accidentally press the wrong key or click the wrong place on a page, we monitor the events over a period of samples. Each event sample consists of $n = 8$ events. If more than $p = 25\%$ of the sample is classified as being off-task, then the entire sample will be classified as off-task. For example, if the student has 7 events that are classified as being on-task and 1 event that is classified as being off-task, this 1 event is ignored and the student is classified as being on-task.

The inequality used to determine when a series of events is on-task is shown in Equation 1. The subset of n sequential events is categorized by E which is defined as $\{x_m + x_{(m+1)} + \dots + x_{(m+(n-1))}\}$,

where x is an event, m is the initial event in the series, and n is the total number of events observed in the series. Each event that effectively executes a function according to Table 1 yields a value of 1, and each event that does not execute a function yields a 0. Equation 1 is computed at every sample until there is no longer a subset of n events to evaluate.

$$\frac{1}{n} \sum_{i=m}^{m+(n-1)} x_i < p \quad \text{OR} \quad \frac{1}{n} \sum E < p, \quad (1)$$

$$\forall m = 1, 2, \dots, n.$$

Eye Gaze

In Asteriadis et al. [13], six user-states were defined for an e-learning environment to categorize if the user was attentive, full of interest, frustrated, distracted, sleepy, and not paying attention. We combined these categories to form two basic user-states – engaged and disengaged. Attentive, full of interest, and frustrated are classified as engaged, while distracted, sleepy, and not paying attention are classified as disengaged. While it might not seem that a user state of frustrated should be classified as engaged, it is important to note that one is only frustrated when he or she is dedicating attention to a particular task. More or less, if the user is not engaged or does not dedicate attention to a task, it is impossible to become frustrated. However, frustration typically leads, as a next step, to being disengaged if the focus of frustration is not resolved in a timely manner.

The amount of time that is classified as disengaged, $T_{disengaged}$, will be recorded along with the total time needed to complete the math test, T_{total} . All of this data is used to derive the percent error of Asteriadis et al.’s eye gaze and head pose model as shown in Equation 2.

$$\text{Percent Error} = \frac{T_{disengaged}}{T_{total}} \times 100\%. \quad (2)$$

Hypotheses

Two hypotheses were developed for our system based on the current research that

measures behavioral user state through eye gaze and head pose.

Hypothesis 1

The student is engaged if his or her series of events (or combination of events) are classified as:

- a) On-task and correct (regardless of speed)
- b) On-task, slow or average, and incorrect

Hypothesis 2

Eye gaze and head pose will not be an accurate measure of user state/engagement for the high difficulty questions. The use of pencil and paper will create false-negatives since eye gaze will be directed elsewhere, such as towards scratch-paper, instead of the computer screen.

Experimental Design

To explore the trends developed over time associated with engagement in CBE, we designed and conducted a pilot study in which participants completed a computer-based math test of varying difficulty. A total of 13 participants took part in this experiment and all were recruited middle school students from an afterschool program in Atlanta, GA. The population consisted of both females and males in the age range of 10-14 years old (Male: 6, Female: 7; Sixth grade: 2, Seventh grade: 5, Eighth grade: 6).

The evaluation consisted of two segments to assess how well the engagement model performed when compared to eye gaze techniques. The initial validation of the engagement model's performance consisted of analyzing the 9 questions of low difficulty, which required low-level cognitive thinking. This segment was directly followed by analyzing the 6 questions of high difficulty, which required high-level cognitive thinking. Each student was given no prior information of the material presented on the tests; however, the questions were taken from the state of Georgia's

Criterion-Referenced Competency Tests (CRCT) [18]. The level of difficulty was determined by the CRCT ranking of each question.

The students were placed in a normal testing environment within a school, as shown in Figure 1. Due to the size of the classroom, all 6 males were tested as the first group followed by 6 of the females. An additional female was tested alone. They were instructed to be engaged throughout the test. The instructions provided to the student followed the following format:

“You will take a 15-question math test. It does not matter how well you perform, and I do not expect you to know all of the answers. However, it is important that you stay focused on each question, give it your best effort, and avoid being sidetracked.”



Figure 1: This is the small classroom where all the testing took place. The maximum amount of students testing were 6 students, and each student had their own laptop, pencil, and scratch-paper.

Each student was provided pencil and paper, which was placed next to the keyboard and mouse; however, the students were allowed to move the pencil and paper as they pleased. The recorded mouse and keyboard events were then analyzed to determine total time, response accuracy, and proper event execution.

We designed three 15-question math tests to assess our hypotheses – one for each grade level. The basic layout of each test is as shown in Figure 2. Boardmaker Plus is the software that was used to create the math program [19]. The tests were designed for students between the 6th and 8th grade. Nine questions on the test were low difficulty and required low-level cognitive thinking to complete. Most, if not all, of those problems can be computed quickly using mental math because they only require one processing step to answer. However, 6 questions were high difficulty and required high-level cognitive thinking to complete. Most, if not all, of those problems cannot be computed quickly using mental math because they require multiple steps to answer. In many cases, pencil and paper may be needed to develop an answer.

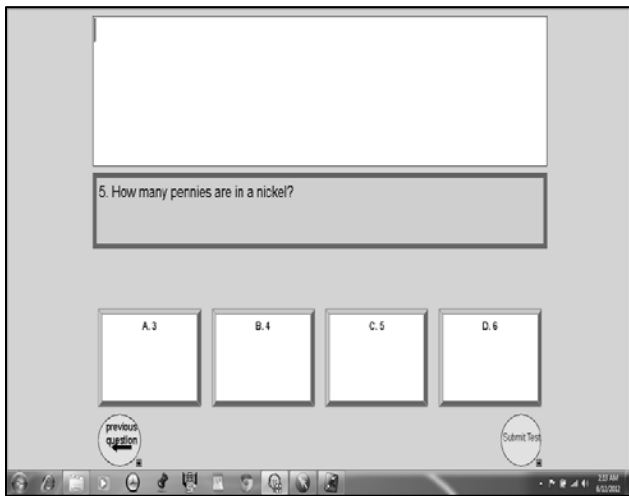


Figure 2: The basic layout of each question on the math test is shown. At the top of the interface, the student was able to type the answer into a textbox. The question was stated in the center of the screen within a green box. Below the question, the multiple-choice selections were displayed as rectangular buttons.

We then used a web camera to monitor eye gaze and pose, which was used to estimate behavioral user state throughout the test. The camera was also used to perform video observations once the test had been completed. A program was used simultaneously to monitor and record the associated mouse and keyboard events.

Results

When analyzing the results, we took all the engagement metrics into consideration, total time, response accuracy, and proper function execution, as well as eye gaze and the exit survey. Table 2 summarizes the data collected using the proposed engagement model (labeled as On-task in the table) as compared to the eye gaze technique.

Table 2: Summary of Results.

Grade & Difficulty	Avg. Score	Avg. Time	On-task	Eye Gaze
6 th	57%	13min	93%	76%
Low	50%	36s	100%	
High	67%	81s	83%	
7 th	39%	10min	96%	59%
Low	44%	29s	100%	
High	30%	59s	90%	
8 th	46%	15min	98%	65%
Low	46%	33s	100%	
High	45%	101s	94%	

Total Time

The total time needed to complete each question was calculated and shown in Figure 3 for the 7th and 8th grade. Because there were only two students in the 6th grade, all of their responses were automatically classified as being of average speed. Using a boxplot, we were able to properly divide the remaining data into its respective quartiles and categorize any outliers as slow or fast. Due to the nature of the box and whisker plot, there will always be a similar distribution between the average, slow, and fast categories as shown in Figure 4c.

Response Accuracy

The students answered 45% of the question correctly and 55% of the questions incorrectly as shown in Figure 4d. This was expected due to the difficulty of the testing material.

Proper Function Execution

Each subject was given the choice to use either the keyboard or mouse to select his or her response. In the results, 4% of the keyboard and

mouse input was classified as being off-task as shown in Figure 4b. By using Table 1, we were able to determine if the mouse clicks and keystrokes occurred within the necessary constraints to successfully navigate through the test. Figure 4a shows the combinations of events that model engagement and how often each combination occurred during this study.

Eye Gaze

Through use of Equation 2, the eye gaze and head pose technique had an average of a 24.2% error for the 6th grade test, a 41.1% error for the 7th grade test, and a 34.8% error for the 8th grade test. Here, the term *error* refers to the amount of time the head pose and eye gaze technique

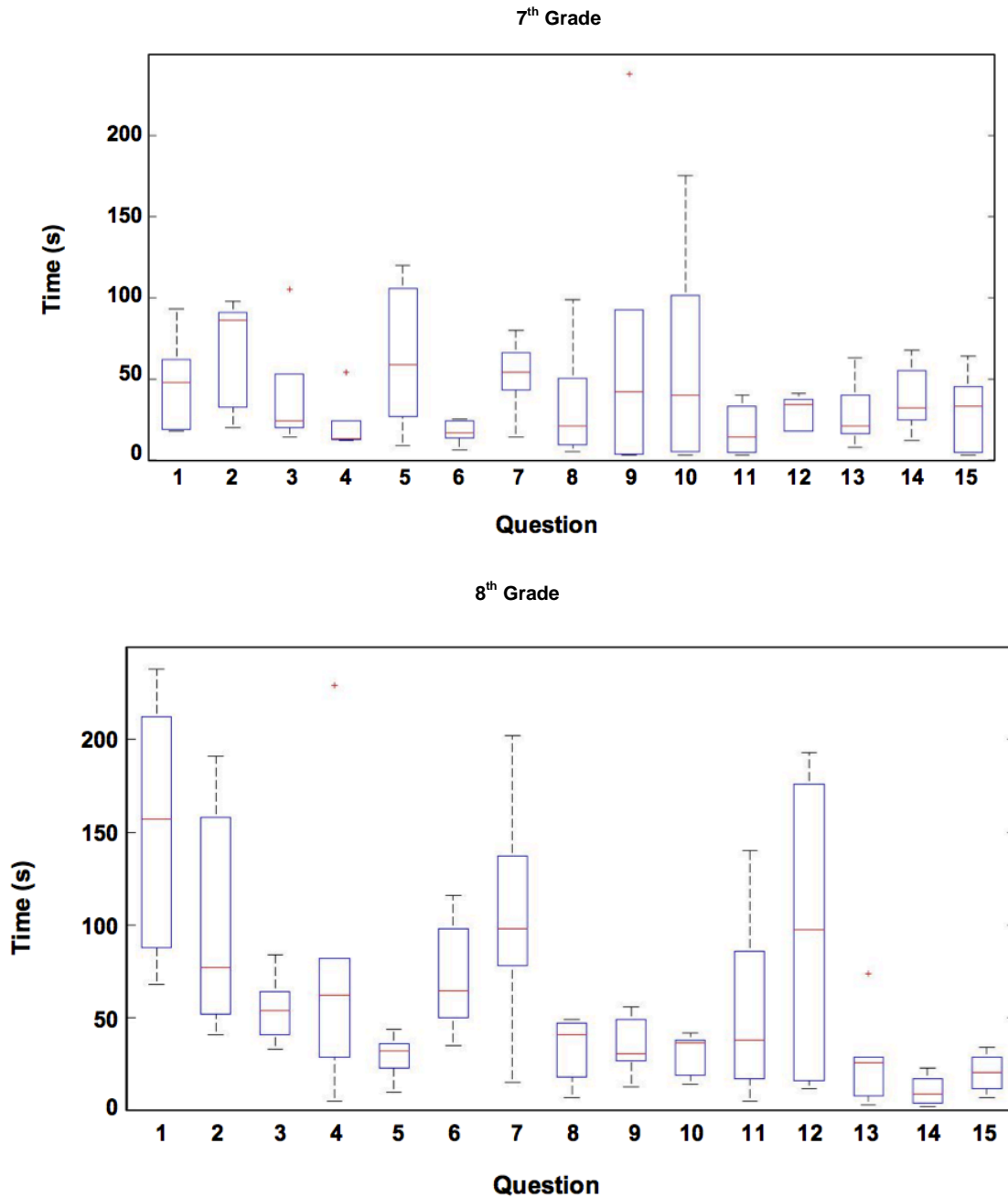


Figure 3: Total time required per question for 7th grade (top) and 8th grade (bottom).

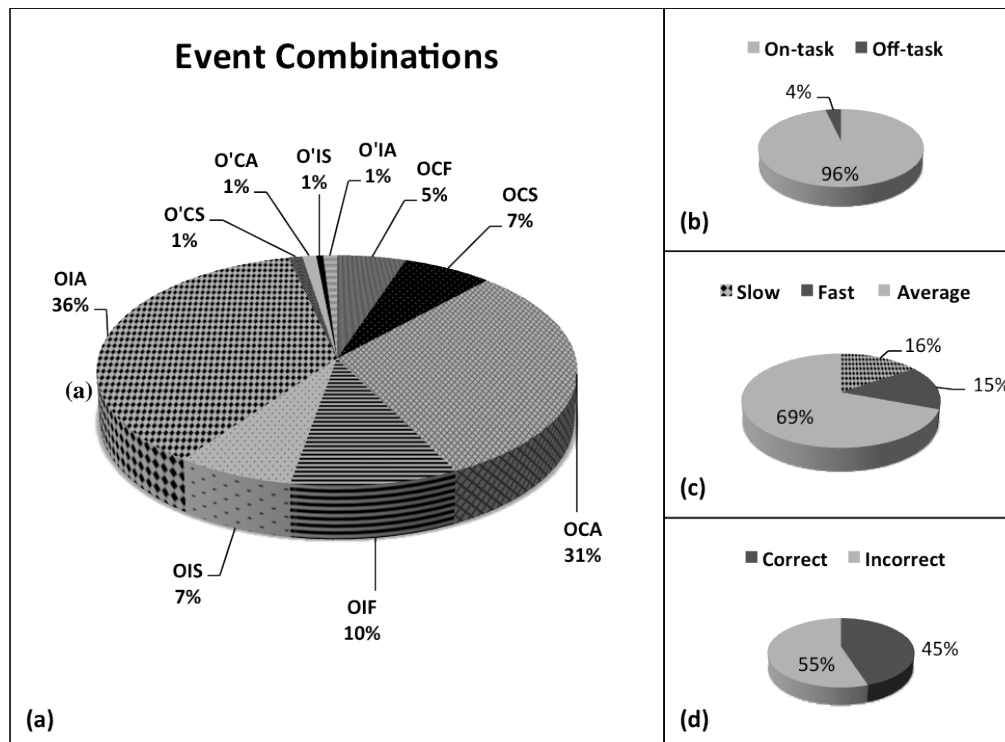


Figure 4: (a) This chart shows how often we received each combination of events (S=slow, A=average, F=fast, C=correct, I=incorrect, O=on-task, O'=off-task). (b) O vs. O' events. (c) Speed of responses. (d) C vs. I responses.

discussed in [13] categorized the student as either distracted, sleepy, or not paying attention. This error suggests that the eye gaze and head pose is not the best measure of engagement. In addition, for the students who scored considerably higher than their peers, they exhibited up to a 65% eye gaze error. Fig. 5 shows the relationship between the subject's test score and the amount of time his or her gaze was not directed towards the screen.

Exit Survey

Following the math test, 5 questions were asked about each question. Three of the questions were based on a 5-level Likert scale, one required a yes/no response, and the last was multiple-choice. Table 3 shows the results of the 3 Likert questions, and the mean and standard deviation are computed based on 195 samples (13 students \times 15 questions).

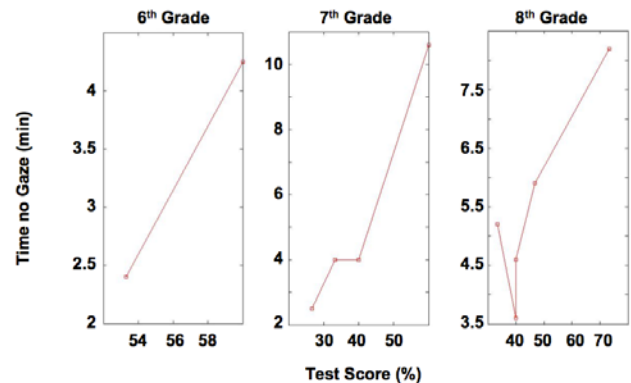


Figure 5: This graph shows the relationship between the subjects' test scores and the amount of time that eye gaze was not on the computer screen.

Table 3: Statistical Analysis of Exit Survey.

Statement	<i>m</i>	SD
I was engaged	3.96	1.40
I understood the question	3.71	1.38
I knew how to solve the problem	3.56	1.41

Overall, the students agreed that they were engaged for each question in the complete test with an average score of 3.96 (Agree = 4, SD =

1.40). They agreed that they understood the questions with an average score of 3.71 (Agree = 4, SD = 1.38). Lastly, the students agreed that they knew how to solve the problems with an average score of 3.56 (Agree = 4, SD = 1.41).

Table 4 shows the results of the multiple-choice question that asked how each answer selection was decided. The options were either that the student made a random guess, an educated guess, or no guess/solved the problem. This may also give some insight on how well the students believed they understood each question and, furthermore, reflect their confidence level.

Table 4: Student’s Confidence of Response.

Selected Response	Total	Percentage
Solved	101	52%
Educated guess	53	27%
Random guess	41	21%

Lastly, Table 5 shows that the students on average used pencil and paper to solve the problems 56% of the time.

Table 5: Student’s Use of Pencil & Paper.

Needed Pen & Paper?	Total	Percentage
Yes	109	56%
No	86	44%

Discussion

Across all students/tests, less than 5% of the samples were classified as being off-task, which is statistically significant (Figure 4b). This suggests that there is a direct correlation between an engaged student and our method of calculating on-task events. Moreover, if a student is classified as being on-task, he or she is engaged (regardless of speed and/or response), which proves Hypothesis 1. However, more tests need to be conducted to verify this assumption.

Furthermore, validity of responses alone is not enough information to determine user-state as exhibited in Figure 4d. Speed coupled with the validity of responses can help to determine more information about the engaged student. If the

student is on-task and has a series of fast responses with a series of correct answers (OCF), the student may need questions of higher difficulty. The results show that 6% of the sample was OCF. If the student is on-task and has a series of slow responses with a series of correct answers (OCS), the student may understand the material and require more time to think. The results show that 7% of the sample was OCS. If the student is on-task and has a series of slow responses with a series of incorrect answers (OIS), the student may lack understanding and need questions of lesser difficulty. The results show that 7% of the sample was OIS. This additional information will be used in the future to better integrate instructional scaffolding and adaptation with the device.

This work also suggests that eye gaze and head pose technique is not an effective measure of engagement when high-level cognitive thinking is required, which supports Hypothesis 2. Based on the video observations performed post-testing, the subjects consistently looked down at the paper to write out the multistep problems and calculate the answers by hand. The use of pencil and paper was further documented by the students in the exit survey (Table 5). We also observed that other subjects looked at random objects in space to perform mental math. In fact, we observed that the longer that the student looked away from the computer screen, the higher he or she performed on the test. The 8th grade subject who scored the highest looked away from the screen for 8.2 minutes, which was 47.4% of the entire test time. The 7th grade subject who scored the highest looked away from the screen for 10.6 minutes, which was 65.4% of the entire test time. The large time delay associated with the lack of eye contact from the human to the computer screen caused Asteriadis et al.’s eye gaze technique to incorrectly declare the subjects as being distracted or disengaged. However, using our engagement model, we were able to correctly categorize the students as being engaged. By monitoring the time delay/speed, accuracy of responses, and proper event execution

associated with each question, we are able to expand the eye gaze model proposed by Asteriadis et al. and apply it in a complex problem solving environment [12].

Conclusions

This investigation is only a starting point for where we would like to go in the future. We have developed a non-invasive approach to classify engagement based on keyboard and mouse input; however, there are cases when the model will fail. For example, when the student has taken a long time to input a response, this model would consider the subject to be engaged and assume that the student is either thinking or working the problem out on pencil and paper. What if the student is actually talking to a peer and still manages to submit an answer before the computer categorizes him or her as disengaged? For situations like this, we would like to integrate a robotic platform into this intelligent tutoring system to reinforce engagement.

Also, now that a model of engagement is created and we are able to accurately determine behavioral user state, we need to implement a method for adaptive tutoring. By utilizing behavioral strategies to maintain the student's attention when engagement decreases, we will be able to keep the students engaged for longer periods of time. Possible behavioral strategies to implement include, but are not limited to gestures, expressions, eye contact, posture, proximity, tone, pitch, and volume.

Future Work

This investigation is only a starting point for where we would like to go in the future. We have developed a basis to what engagement looks like with keyboard and mouse input; however, there are cases when the model will fail. For example, when the student is taking a long time to input a response, this model would consider the subject to be engaged and assume that the student is either thinking or working the problem out on pencil and paper. What if the student is actually talking to a peer and still

manages to submit an answer before the computer categorizes him or her as disengaged? For situations like this, we would like to integrate a robotic platform into this intelligent tutoring system to reinforce engagement.

More specifically, the long-term goal is to create an adaptive robotic tutor using a humanoid robot in conjunction with a touchscreen device. Therefore, we would like to conduct a similar experiment that will effectively transfer the mouse/keyboard model to a touch-screen device. The mouse clicks will be comparable to a stylus and/or touch screen. The physical keyboard events will be comparable to the events of a virtual keyboard. Mouse movements, which are evident in the CBE setting, will be obsolete once the robotic platform with touchscreen capabilities is utilized.

Also, now that a model of engagement is created and we are able to accurately determine behavioral user state, we need to implement adaptive tutoring. By utilizing behavioral strategies to maintain the student's attention when engagement decreases, we will be able to keep the students engaged continuously. Possible behavioral strategies to implement include, but are not limited to gestures, expressions, eye contact, posture, proximity, tone, pitch, and volume.

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