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Exploration of Student Online Learning Behavior and Academic Achievement

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EXPLORATION OF STUDENT ONLINE LEARNING BEHAVIOR AND ACADEMIC ACHIEVEMENT

by

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Abstract

Students' online persistence has typically been studied at the macro-level (e.g., completion of an online course, number of academic terms completed, etc.), and was investigated as a dependent variable with predicting variables such as motivation, engagement, economical support, etc. This study examines students' persistence in an online adaptive learning environment called ALEKS, and the association between students' academic achievement and persistence. With archived data that included students' online math learning log and standardized tests scores, we first explored students' learning behavior patterns with regard to how persistent they were while learning with ALEKS. Three variables indicating three levels of persistence were created and used for cluster analysis. Hierarchical clustering analysis identified three distinctive patterns of persistence-related learning behaviors: (1) High persistence and rare topic shifting; (2) Low persistence and frequent topic shifting; and (3) Moderate persistence and moderate topic shifting. We further explored the association between persistence and academic achievement. Analysis of covariance (ANCOVA) indicated no significant difference in academic achievement between students with different learning patterns. This result seems to suggest that "wheel-spinning" coexists with persistence and is not beneficial to learning. This finding also suggests that ALEKS, and other intelligent learning environments, would benefit from a mechanism that determines when a student fails that takes into account wheel-spinning behaviors. This would allow for a more appropriate intervention to be provided to learners in a timely manner.

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Chapter 1

Introduction

The study reported in this thesis is based on the observations of a self-paced after-school mathematics program. The data is computer records of students' interaction with a mathematics learning system called ALEKS (Assessment of LEarning in Knowledge Space). ALEKS is one of the most widely used online adaptive learning systems, with millions of users all over the world. The difference between traditional web-based learning systems and adaptive learning systems is that adaptive learning systems tailor their service to individual users (Brusilovsky, Karagiannidis & Sampson, 2004). An adaptive learning system typically collects students' data and uses it to create a student model. The student model is then used to adapt the presentation and navigation of the learning material (Brusilovsky, 1999). With more adaptive learning systems being built, researchers have pointed out the importance of evaluating adaptive learning systems for further improvement and generalization (Brusilovsky et al., 2004). As one of the popular adaptive learning systems, ALEKS was evaluated in some empirical studies which were carried out in different settings, and was observed to be effective in most of the studies (Craig et al., 2013; Fanusi, 2015; Fullmer, 2012; Grenier, 2013; Hagerty & Smith, 2005; Hu, Luellen, Okwumabua, Xu & Mo, 2007; Mertes, 2013; Nwaogu, 2012; Palocsay & Stevens, 2008; Taylor, 2008; Xu, Meyer & Morgan, 2009). The average effect size of ALEKS was 0.5, which is higher than some of the more popular online mathematics tutoring systems such as Cognitive Tutor (Fang, Ren, Hu & Graesser, 2017). These studies generally measured ALEKS students' learning gains or academic achievements; however, none of them looked at students' learning process, or online learning behaviors. The data analyzed in this study is from one empirical experiment that evaluated the learning efficacy of ALEKS. We collected both offline learning outcomes and online learning sequences, and explored students' online learning behaviors and the relationship between specific learning behaviors and learning outcomes.

To better describe the study in this thesis, I will briefly introduce ALEKS and the theory it is based on and provide a brief background of literature on persistence in different academic settings.

ALEKS

ALEKS is an online intelligent tutoring system built based on Knowledge Space Theory (Falmagne, Koppen, Villano, Doignon & Johannesen, 1990). On the ALEKS website, the knowledge space theory was described as a mathematical language developed to delineate the ways in which particular elements of knowledge (concepts in Algebra, for example) can be gathered to form distinct knowledge states of individuals (ALEKS Corporation, 2016a). In ALEKS, student models are created in the form of knowledge states, and these student models are used to guide the presentation of the course material to students. According to Knowledge Space Theory, a knowledge domain is represented by a finite set of concepts. The knowledge state of a student in a domain can be represented by a particular subset of concepts that the student is capable of mastering. For instance, Algebra I in ALEKS is regarded as a domain of approximately 700 basic concepts, which give rise to a structure of millions of empirically feasible knowledge states. Inner fringe and outer fringe are two key concepts in knowledge space theory, which are essential for creating a student model. Inner fringe is the set of concepts that a student has mastered, and outer fringe is the set of concepts a student is ready to learn (Falmagne, Cosyn, Doignon & Thiéry, 2006). By gauging learner's knowledge state, ALEKS determines what a student knows and is ready to learn, and provides personalized learning paths that are ideal for each student (Albert & Lukas, 1999).

ALEKS starts with an individualized initial assessment to find a new student's knowledge state. The assessment usually consists of 20 to 30 problems (out of more than 600 problems). The assessments are adaptive, in the sense that the problem provided depends on the accuracy of the student's answer on the previous problems. Therefore, the assessment problems are not the same for all student. After the initial assessment, the student receives a report in a color-keyed pie chart (as shown in Figure 1). Each "slice" of the pie chart corresponds to a particular area of the syllabus, such as "decimal numbers" or "proportions and percents" and each

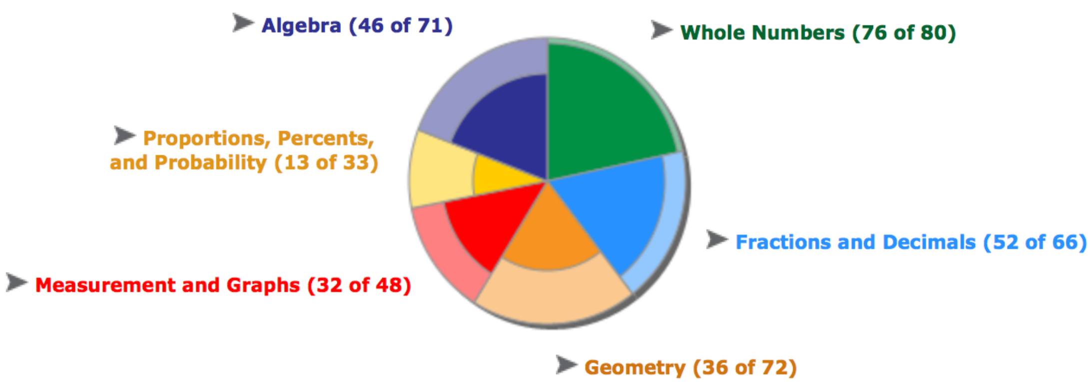

Figure 1. ALEKS knowledge pie showing number of concepts learner has learned and needs to learn

slice has a darker shade of color indicating how much the student has mastered in that area (ALEKS Corporation, 2016b). After the first assessment, ALEKS identifies the student's knowledge state and generates a list of topics the student is ready to learn in each area. Once a student chooses the area and topic he/she wants to work on, ALEKS will provide a set of problems, and the student learns by solving problems under a specific topic. For each problem, there is an "Explain" button which provides the worked example with detailed explanations to the problem. After successfully solving problems covering the same topic, the system will determine a student's mastery of the topic and the student can then move onto a new topic

(ALEKS Corporation, 2016c). ALEKS has periodical assessments, the results of which keep adjusting the student's knowledge state. If a student has already mastered a topic but does not answer the problems under that topic correctly in the assessment, the mastered topic will be removed from his/her knowledge state, and he/she must go back and relearn the topic. This ensures the retention of learned topics in long term memory (ALEKS Corporation, 2016d).

"ALEKS is based on the understanding that students learn math in different ways, and at differing speeds" (Fanusi, 2015). Each student has their own set of concepts that he/she is ready to learn and can choose from, thus each student can set up his/her own pace and choose the topics he/she prefers to work on. There are two modes in ALEKS: learning mode and review mode. Within the learning mode, students can access "practice problems, explanations of problems, worksheets individualized for each student's knowledge, an ALEKS calculator (when appropriate), feedback, progress monitoring" (Fanusi, 2015). Within the review mode, students work on the topics they have already mastered to reinforce their knowledge. A student learns through solving the given problems or reading explanations. When the student is not sure about how to solve a problem, or answers incorrectly, he/she can hit the "Explain" button and read a detailed explanation. Even after solving a problem or mastering a concept, the student can still read the explanation to reinforce his/her knowledge. Once the student consistently solves the problems for a given topic correctly, ALEKS considers that the student has learned the topic and the student can choose another topic to learn. As the student masters new topics, ALEKS updates his/her knowledge pie (ALEKS Corporation, 2016e). The student's knowledge state is changed at that point, and new sets of topics are added to what he/she is now ready to learn.

Persistence and Academic Achievement

In this section, we will introduce how persistence has been studied in different learning contexts--traditional classroom environment and online learning environment, and how the relationship between persistence and academic achievement has been investigated. While "persistence" has been given different meanings in different studies, we are going to explore the differences and define persistence in our study. We will develop our research questions centered around the relationship between persistence and academic achievement.

Persistence is "the quality that allows someone to continue doing something or trying to do something even though it is difficult or opposed by other people" (Merriam-Webster's collegiate dictionary, 2003). According to Rovai (2003), persistence is the behavior of continuing action despite the presence of obstacles. Persistence in the face of adversity is often described as a result of high motivation. For instance, in the literature investigating classroom learning, persistence was typically examined as an outcome factor of motivation. Elliot and his colleagues (1999) found mastery goals and performance approach goals were positive predictors of persistence; Vansteenkiste et al. (2004) found intrinsic motivation improved student persistence; Multon, Brown and Lent (1991) proved that self-efficacy facilitated persistence. Although the concept of persistence was studied in different literature, it was operationalized in various ways. For example, in the meta-analysis by Multon and his colleagues (1991), they summarized three ways of operationalizing persistence after viewing eighteen studies-- time spent on task, number of items or tasks attempted or completed, and number of academic terms completed. Apart from these three commonly used measures, persistence was also frequently measured with self-reports (Agbuga & Xiang, 2008; Elliot, Mcgregor & Gable, 1999; Xiang & Lee, 2002).

In the context of online learning environment, persistence was usually defined as the completion of an online course, or an antonym of attrition (Finnegan, Morris & Lee, 2009; Hart, 2012; Morris, Finnegan & Wu, 2005; Park & Choi, 2009; Rovai, 2003). Persistent learners, who were referred to as "completers", were the learners who successfully completed an online course. Non-persistent learners, who were referred to "dropouts", were the learners who did not finish a course (Finnegan, Morris & Lee, 2009; Hart, 2012). Persistence was mainly explored as a dependent variable affected by psychological and social factors, such as self-motivation, engagement, economic support, etc. (Hart, 2012). Persistence was also investigated as a consequence correlated with online behaviors such as participation, discussion, etc. (Morris, Finnegan & Wu, 2005; Rafaeli & Ravid, 1997).

Although the context of this study was online learning environment, we did not investigate persistence as whether students finished an online course, which was how persistence was typically examined. The reason is for the after-school program in which students learned math with ALEKS, there was no specific standard of completion. Students started at different times and participated for different amounts of time in each session, and got different tasks due to different knowledge states. In order to keep students from dropping out, the after-school program provided students snacks and games during the break, thus the motivation for participation might have been rewards rather than learning. Due to these factors, the macro-level persistence, such as completion of a course, was not an appropriate measure for our study. Therefore, we studied persistence from micro level by looking at students' learning behaviors in each individual task. Rovai (2003) referred to persistence as "continuing action despite the presence of obstacles". Therefore, we looked at whether students continued action and how much they continued while facing obstacles. We not only looked at the effort students put into each individual task, but also looked at the results of the tasks. If the student did not put enough effort and ended up failing the task, we defined such learning behaviors as low persistence. If the students put an appropriate amount of effort, we defined the learning behaviors as either medium or high persistence based according to the specific amount of effort.

Relationship between Persistence and Academic Achievement

Despite various studies on persistence in learning, persistence was rarely studied as a predicting factor. Stekel and Tobias (1977) hypothesized a curvilinear relationship between self-estimated persistence and achievement. They predicted a moderate amount of persistence would lead to the highest achievement. They also hypothesized that persistence would be positively related to achievement in lecture-related instructional environment, but unrelated in the individualized instructional environment. However, they failed to prove their hypotheses. While examining the mediation effect of persistence on the relationship between goals and academic achievement, Elliot et al. (1999) found self-reported persistence was a positive predictor of exam performance in lecture-based classroom setting. This proved one of Stekel and Tobias' hypotheses. For adaptive online learning system like ALEKS, the instructional context could be considered individualized because ALEKS models student's knowledge state and always provides the concepts students are ready to learn. In an individualized learning environment like ALEKS, we wonder whether persistence is unrelated to academic achievement, as hypothesized by Stekel and Tobias (1977). To answer this question, we explored students' persistent learning behavior patterns in ALEKS, and tried to find whether they were related to academic achievement.

Our primary goal of this study is to identify persistent learning patterns. In online learning environment, one approach used to classify learners' behavior patterns was cluster analysis (Bluic, Ellis, Goodyear & Piggott, 2010; Del Valle & Duffy, 2009; Wise, Speer, Marbouti & Hsiao, 2013). Cluster analysis partitions data sets into clusters so that the data points in a cluster are more similar to each other than points in different clusters (Guha, Rastogi & Shim, 1998). For example, Wise et al (2013) clustered learners' online listening behaviors, and found three distinct patterns of behaviors. The learners with those three patterns were superficial listeners, broad listeners and concentrated listeners. In our study, we examined students' persistent learning behaviors in ALEKS to identify distinctive persistent learning patterns. Another goal of this study is to explore the relationship between persistence and academic achievement. This study is not an experimental study; thus we are not able to explore the causal relationship. Instead, our goal is to see whether persistence and academic achievement are correlated in individualized learning environments like ALEKS.

Chapter 2

Methods

In this section we will first introduce the experiment and the data sets used, and then we will explain in detail how the data was processed and the techniques that were used to perform statistical analyses.

Data Sets

The data sets used for this study were collected from Jackson-Madison Intelligent Tutoring System Evaluation (JMITSE) program. JMITSE was an after-school program applied in five middle schools in Jackson-Madison County School System of Tennessee from 2009 to 2012. The goal of JMITSE program was to investigate whether technology outperformed human teachers in math teaching. There were two experimental conditions: teacher condition and technology condition. In the teacher condition, students learned math with math teachers in the after-school program. In the technology condition, students learned math with ALEKS. For this study, we only used data from the ALEKS condition. The program lasted for three academic years and 366 sixth-graders were assigned to the ALEKS condition altogether. Participants were supposed to study for two 1-hr sessions every week, for 25 weeks. Logs of all students' online learning activities were recorded by the system. The ALEKS log file included students' online ID, the topics (i.e., concepts) students attempted, learning mode (i.e., learning, review), time elapsed and the result of each attempt. Table 1 is a sample log file. For each attempt, there are five possible results: correct, wrong, explain, added to pie and failed. "Correct" is shown after a learner attempts a task and gets the correct answer. "Wrong" is shown after a learner attempts a task and gets a wrong answer. After a learner gets a wrong answer, two buttons "Try" and "Explain" will be shown to the learner. If the learner hits the "Try" button, he/she will be given

Table 1

A Student's Learning Log Sample in ALEKS System

Student	Date	Time	Mode	Topic	Result
20110100451	10/23/11	4:17:22 PM	Learning	Drawing lines of symmetry	Explain
20110100451	10/23/11	4:18:04 PM	Learning	Drawing lines of symmetry	Correct
20110100451	10/23/11	4:18:54 PM	Learning	Drawing lines of symmetry	Wrong
20110100451	10/23/11	4:19:10 PM	Learning	Drawing lines of symmetry	Explain
21111104768	03/25/12	3:09:04 PM	Learning	Perimeter of a polygon	Correct
21111104768	03/25/12	3:10:01 PM	Learning	Perimeter of a polygon	Correct
21111104768	03/25/12	3:10:58 PM	Learning	Perimeter of a polygon	Correct
21111104768	03/25/12	3:12:01 PM	Learning	Perimeter of a polygon	Added to Pie

another problem to work on. If the learner hits the "Explain" button, a worked example of that problem will be provided (as shown in Figure 2). Reading an explanation is regarded as an attempt and the result is recorded as "Explain." "Added to Pie" is shown after learner attempts a problem correctly. The difference between "Added to Pie" and "Correct" is that "Correct" is based on one single attempt, but "Added to Pie" is based on multiple correct attempts. When a learner can correctly answer problems under a concept consistently, ALEKS decides the learner has mastered the concept and adds the concept to the learner's knowledge pie. After being added to the knowledge pie, that topic will not be given to the learner again, except for reviewing. "Failed" is shown after a learner attempts a task and answers incorrectly. Similar to "Added to Pie", it is not merely based on one single attempt, instead, it happens when there are multiple unsuccessful attempts and the system decides that the learner failed to learn that topic.

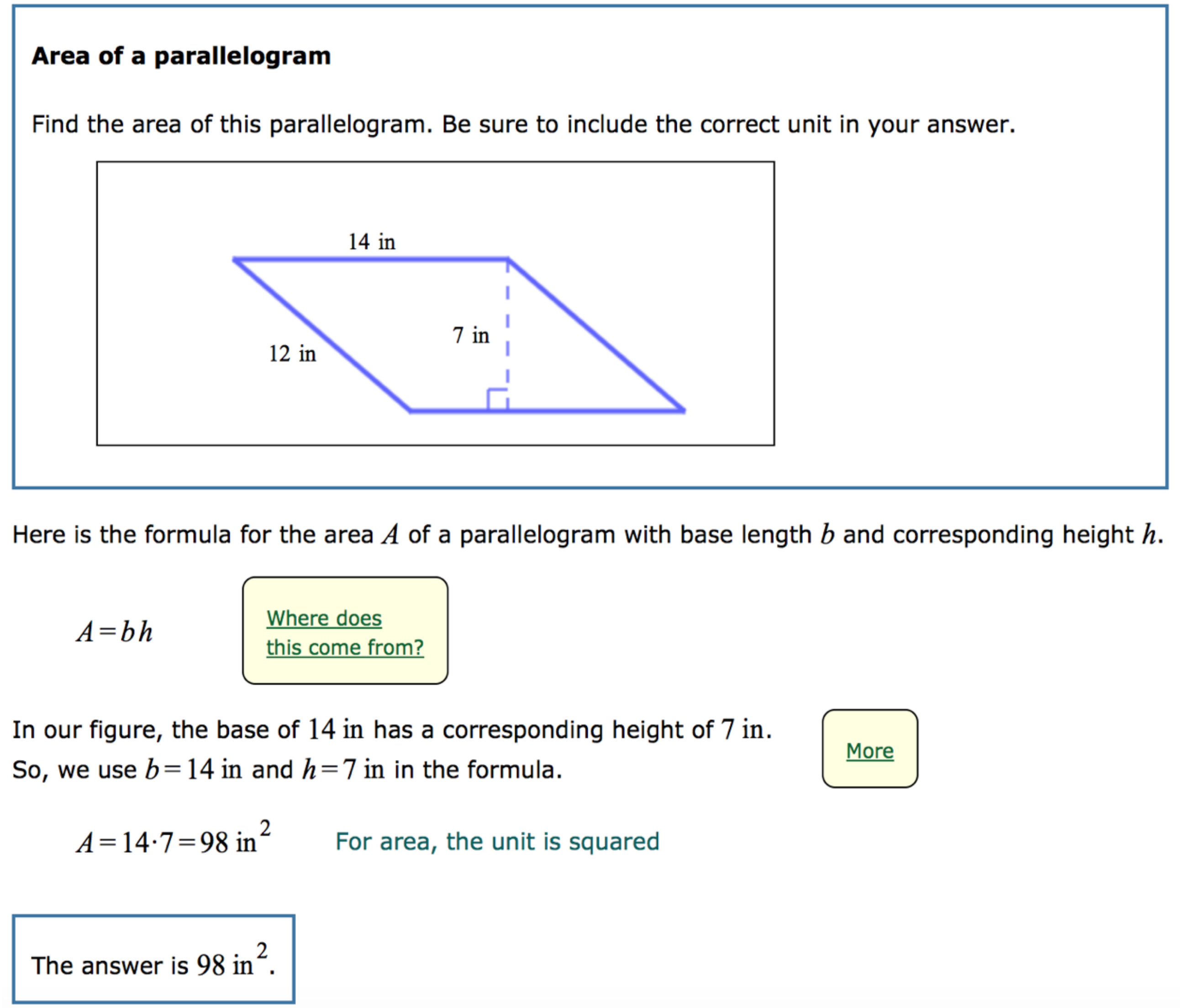

Figure 2. An ALEKS worked example shown in explanation

The participants of JMITSE took the Tennessee Comprehensive Assessment Program (TCAP), which is a standardized test, twice. Before entering the program, the students took TCAP5, which was TCAP for 5th graders. After finishing the program, the students took TCAP6, which was TCAP for 6th graders. The two tests were used as pretest and posttest in the analysis.

Data Processing and Analysis

The log file used in this study contains 330,319 lines of online learning sequence from 366 students. Each line represents an attempt from a student on one topic. Most students attempted multiple topics, and most topics were attempted multiple times. Therefore, for each student, there were multiple rows of data. Firstly, the data was aggregated at topic level. After aggregation, the number of observations for each individual student equaled to the number of topics they attempted. For each topic attempted by a student, we computed the number of attempts and amount of time spent on the topic, as well as whether it was mastered. After the first aggregation, there were 51,982 rows in the new data set. For the new data set, we created three variables: “Mastered”, “Attempts” and “Time”. Variable “Mastered” was dummy coded. For each topic attempted by a student, if “Added to Pie” was in the learning sequence of a topic, it was coded 1. Otherwise, the topic was coded as 0. “Attempts” was the number of attempts a student spent on a topic. “Time” was the time a student spent on a topic from the beginning he/she started that topic till h/she left the topic. Both variables were computed from the original log file. Table 2 is a sample of the data after the first aggregation and creation of the dummy coded variables. Both “Attempts” and “Time” could measure the effort a student spent on task. Pearson product-moment correlation coefficient indicated that the two variables were highly correlated (r = .98). To determine which variable to use as the measure of effort, we further examined the distribution of the two variables. The distribution of the two variables revealed that neither of them were normally distributed. However, after log transformation, “Attempts” became approximately normally distributed, but “Time” was still skewed (as shown in Figure 3). Therefore, “Attempts” was chosen to measure student’s effort on task. We created a categorical variable “Effort” after choosing “Attempts” as the measure of effort. “Effort” has three levels

Table 2

A Sample of Data after Aggregated to Topic Level with Newly-created Variables

Student	Topic	Master	Attempts	Time (Sec)
2110100041	Measuring length to the nearest inch	1	5	236
2110100041	Interpreting a Venn diagram of 2 sets	0	18	964
2110100041	Decimal place value: Tenths and hundredths	0	8	323
2110100041	Reading a point in quadrant 1	1	2	142
2110100417	Understanding equivalent fractions	1	14	622
2110100417	Expanded form	1	2	142
2110100417	Introduction to the counting principle	1	9	324
2110100451	Estimating a difference of whole numbers	0	1	0
2110100451	Divisibility rules for 2, 5, and 10	1	2	142
2110100451	Power of 10: Positive exponent	1	9	324

and it was coded based on log-transformed attempts. For each topic, if its log-transformed attempts was in the first quartile of the distribution, it was coded as “low effort”. If it was between the second and third quartile, it was coded as “medium effort”. If it fell into the fourth quartile, it was coded as “high effort”. After creating and coding the effort variable, we created three variables as measures of persistence, and they were named “Switch”, “Moderate persistence” and “High persistence”. All three variables were dummy coded. “Switch” stands for low persistence. We chose “Switch” because it was frequently observed in the log file that when student spent low effort on a topic, they often switched to a new topic after one or two attempts without mastering the topic.

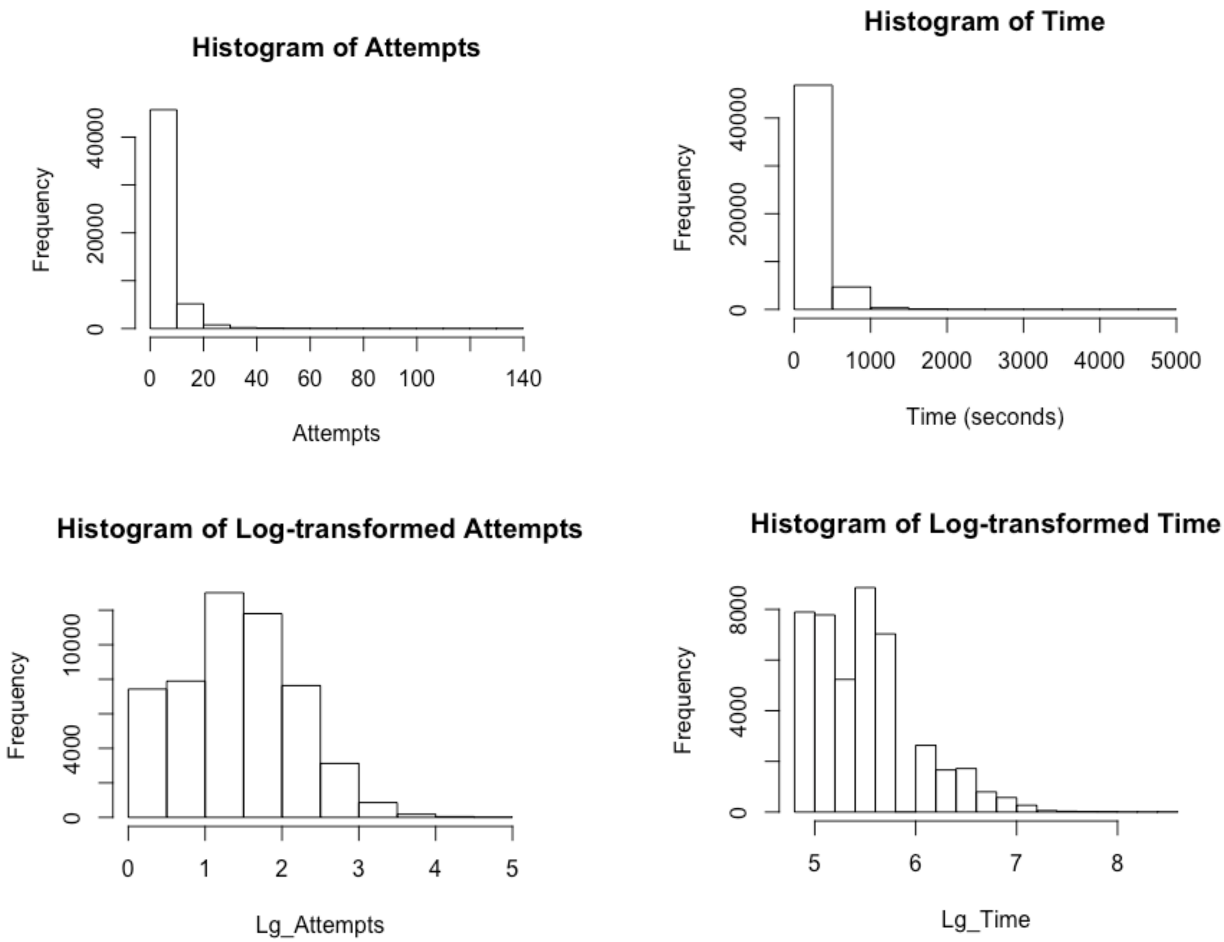

Figure 3. Distribution of attempts on each topic, time on each topic, log-transformed attempts on each topic and log-transformed time on each topic

Therefore, if the effort a student spent on a topic was low, and the topic was not mastered, "Switch" was coded 1, otherwise it was coded 0. "Moderate persistence" was coded 1 when the effort on a topic was medium, otherwise it was coded 0. "High persistence" was coded 1 when the effort on a topic was high, otherwise it was coded 0. Thus, we got three binary variables, "Switch", "Moderate persistence" and "High persistence", for each topic attempted by a student. These variables were used for later analyses. In the next step, the 51,982 rows of data were aggregated to student level by averaging the persistence variables. We got 366 observations in the new data set. Each row stands for a unique student. After aggregation, the three persistence variables became continuous rather than binary. These variables represent the percentage of topics that a student persisted at each level. For instance, if a student gets 0.2 in “high persistence”, it means that the student attempted twenty percent of the topics with high persistence. Lastly, we computed the number of topics each student attempted for data screening. The three persistence variables were percentages, which represented the percentage of topics finished with some level of persistence for all the topics attempted by a specific student. If the total number of topics attempted were too small, it did not necessarily imply certain behavior patterns, even if the percentage for that behavior was high. Therefore, the students whose attempted topics were at the bottom 25% (Topics <= 61) were screened from further analysis. There were 275 observations after screening. Table 3 is a sample of the data after aggregation to student level. After aggregating data to student level, we conducted cluster analysis to explore students’ persistence learning patterns. Cluster analysis has been a statistical technique widely used to understand learner’s behaviors in online learning environment (Bluic et al., 2010; Morris et al., 2005; Wise et al., 2013). In cluster analysis, learners are grouped together based on their similarities across variables.

Therefore, the technique helps determine the learners with similar behavior patterns. After grouping students based on their learning patterns, we performed analysis of covariance to compare academic achievements of students from different groups. We also conducted analysis of variance to compare the number of topics mastered by different groups and percentage of different types of behaviors, to better understand the effect of online behaviors and the association between online behavior and academic achievement.

Table 3

A Sample of Data after Aggregated to Student Level

Student	Switch	Moderate persistence	High persistence	Topics
2110100041	0.15	0.29	0.28	72
2110100417	0.11	0.34	0.2	167
2110100451	0.4	0.27	0.11	150
2110102070	0.22	0.26	0.21	171
2110102919	0.2	0.39	0.18	88
2110103053	0.2	0.34	0.09	199
2110103208	0.25	0.31	0.21	169
2110104421	0.13	0.31	0.1	143
2110104842	0.25	0.4	0.2	313

Chapter 3

Results

Cluster Analysis

There is no strictly defined sample size for cluster analysis. According to the suggestion of Formann (1984), the minimal sample size should be no less than 2^k cases (k = number of variables), preferably $5*2^k$. After screening, the study examined the clustering of 275 observations across three variables, which fell comfortably within the accepted range. Ward's (1963) hierarchical clustering technique was applied and the squared Euclidean distance was used to calculate the distance between clusters. A scree plot was used to determine the optimum number of clusters, where the levelling-off point indicated a reduced variability between clusters after it (Wise et al., 2013). Examination of scree plot (see Figure 4) revealed flattening between three and four clusters, indicating that a three-cluster solution best captured the similarities and differences between students on the three variables. The cluster membership did not change by repeating the

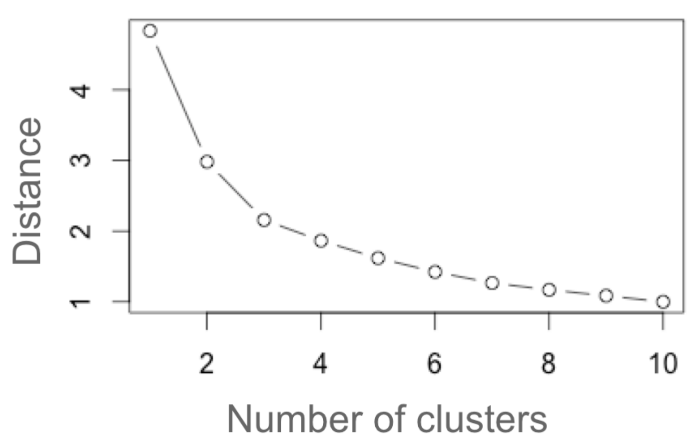

Figure 4. Scree plot for the cluster analysis

analysis, and significant differences were found by conducting ANOVAs for the clustering variables, which further confirmed the quality of the solution. The three-cluster solution is shown in Figure 5. The scales are the percentage of topics students attempted with a specific behavior. For example, the y axis of the top row is the percentage of switch behavior. The x axis of the top middle block is the percentage of

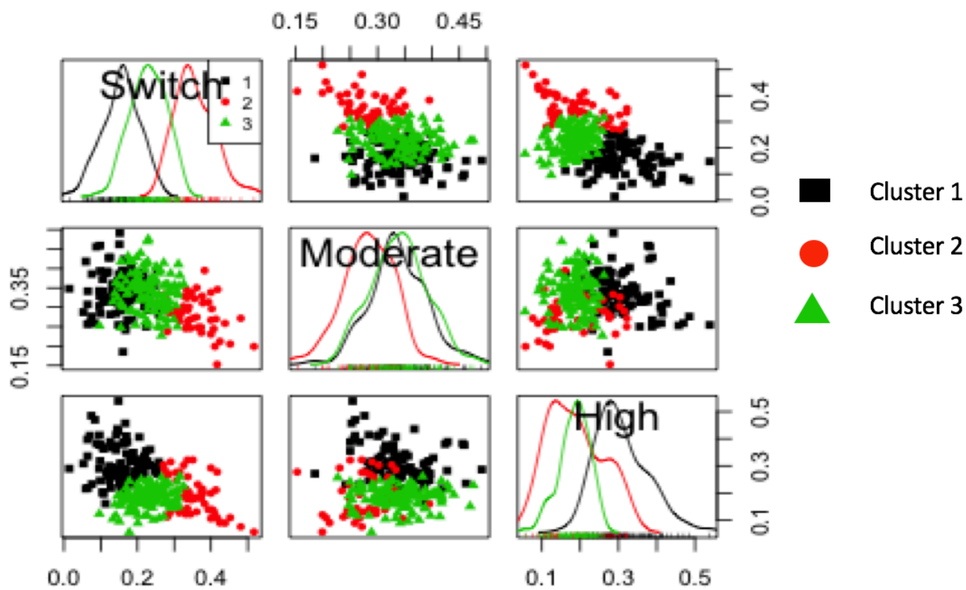

Figure 5. Scatterplot matrices of three-level persistence of the three clusters

moderate persistent learning behavior, and x axis of the top right block is the percentage of high persistent learning behavior. From the top middle block, we can find the clusters are more distinct on switch behavior (i.e., y axis), whereas on the moderate persistence behavior (i.e., x axis) there is more overlap between the student clusters. From the top right block, we can find the black cluster has more high persistent learning behavior, and the green and red clusters have more overlap. The descriptive statistics on the grouping variables and the academic achievement variables, that we further explored, are shown in Table 4.

Cluster 1: High persistence, low switch. Cluster 1 (i.e., the black cluster in Figure 5) accounts for 37.5% of the study sample (n = 103). The students in this cluster switched topics less than members of other two clusters. The switching ratio of cluster 1 is 0.16, which indicates that students quickly gave up or switched to other topics before mastery for 16% of the tasks they attempted. For 34% of the tasks, the students worked with moderate persistence (i.e., attempted the task for 3-7 times). And for 31% of the tasks, the students worked with high persistence (i.e., attempted the task for 8 or more times). These students did not easily give up on tasks, and put a large amount of effort on one third of the tasks they got, which indicated that they were persistent learners.

Table 4

Mean Scores and Standard Deviations for Each Variable by Cluster

	Cluster 1 (n = 103)	Cluster 2 (n = 54)	Cluster 3 (n = 118)
Switch	0.16 (0.05)	0.36 (0.05)	0.23 (0.05)
Moderate persistence	0.34 (0.05)	0.28 (0.05)	0.34 (0.05)
High persistence	0.31 (0.07)	0.19 (0.07)	0.18 (0.04)
TCAP5	46.72 (18.25)	39.37 (17.60)	47.28 (17.23)
TCAP6	43.23 (20.89)	32.69 (18.44)	40.49 (21.63)

Cluster 2: Low persistence, high switch. Cluster 2 (i.e., the red cluster in Figure 5) is a comparatively smaller cluster including 19.6% (n = 54) of the study sample. The distinctive characteristics of this cluster is their high switching ratio. For 36% of the tasks they were given, the learners quickly gave up or switched to new tasks before mastering them. The students worked with moderate persistence (i.e., attempted the task for 3-7 times) on 28% of the tasks. And worked with high persistence for 19% of the tasks (i.e., attempted the task for 8 or more

times). Compared with the other two clusters, the students in this cluster were not very persistent. Although they worked on some tasks with multiple attempts, they gave up on a large percentage of the tasks, and they were not willing to put too much effort on a task.

Cluster 3: Moderate persistence, moderate switch. Cluster 3 (i.e., the green cluster in Figure 5) is the largest cluster with 118 students representing 42.8% of the study sample. The student in this cluster switched topics on 23% of the tasks, which is higher than that of Cluster 1 but lower than that of Cluster 2. They worked with moderate persistence on 34% of the tasks and with high persistence on 18% of the tasks. Compared to the other two clusters, this cluster does not distinctively stand out in any type of behavior. The students gave up a medium portion of topics and worked with high effort on a comparatively low portion of topics. They worked on the tasks with mostly moderate persistence. It seems they were regulating their learning in a rational way in the self-regulated learning environment.

Analysis of Covariance (ANCOVA)

In order to investigate the association between persistence and academic performance, a one-way analysis of covariance (ANCOVA) was conducted to determine a statistically significant difference between three clusters on posttest scores controlling for pretest scores. The effect of cluster on posttest scores after controlling for pretest scores was not statistically significant, $F\ (2,212) = 1.25$, $p = .29$, which means the academic achievement of the three clusters with different behavior patterns were not significantly different from each other.

Analysis of Variance (ANOVA) and Post Hoc Tests

To better understand the effect of online persistent behaviors, a one-way analysis of variance (ANOVA) was conducted to determine a statistically significant difference between three clusters on the number of mastered topics at different difficulty levels. The topics were divided into three levels based on the percentage of students who mastered them. The topics in the first quartile had the highest mastery percentage, which we defined as easy topics. The topics in the second and third quartiles had the medium mastery percentage, and were defined as medium topics. The topics in the fourth quartile, had the lowest mastery percentage, and were defined as hard topics. The numbers of mastered easy topics were not found to be significantly different among three clusters, $F(2,272) = 2.56$, $p = .08$. However, the numbers of mastered medium ($F(2,272) = 9.98$, $p = 0$) and hard topics ($F(2,251) = 8.92$, $p = 0$) were found to be significantly different between clusters. Post-hoc tests indicated that there was no statistically significant difference between cluster one and three on the number of medium and hard topics being mastered. However, both cluster one and three mastered significantly more medium and hard topics than cluster two. The means and standard deviations of mastered topics for each cluster are shown in table 5.

In order to understand why persistence was not related to academic achievement, we further examined the percentage of topics attempted with moderate persistence and high persistence. For clusters one, two and three, the percentages of tasks attempted with moderate persistence without mastery were 0.11 ($\sigma = 0.05$), 0.08 ($\sigma = 0.04$) and 0.07 ($\sigma = 0.03$), respectively. The percentages of tasks attempted with high persistence without mastery were 0.21($\sigma = 0.08$), 0.17 ($\sigma = 0.06$) and 0.16 ($\sigma = 0.06$). Analysis of variance (ANOVA) indicated a significant difference of the unmastered topics attempted with moderate ($F(2, 272) = 30.3$, $p < .001$) and high persistence ($F(2,272) = 14.3$, $p < .001$) among the three clusters. Post-hoc tests indicated Cluster 1 was significantly higher than both Cluster 2 and Cluster 3 in unmastered topics attempted with both moderate and high persistence.

Table 5

Means and Standard Deviations of Three Types of Topics Mastered by Cluster

	Cluster 1	Cluster 2	Cluster 3
Easy topics	24.06 ($\sigma = 12.1$)	22.7 ($\sigma = 12.88$)	27.21 ($\sigma = 15.08$)
Medium topics	49.46 ($\sigma = 26.85$)	33.56 ($\sigma = 18.74$)	51.75 ($\sigma = 26.99$)
Hard topics	16.11 ($\sigma = 13.93$)	6.86 ($\sigma = 6.05$)	14.27 ($\sigma = 12.13$)

Chapter 4

Discussion

To study students' persistence in ALEKS and the relation between persistence and academic achievement, we examined students' learning behavior on each individual task they worked on. With archived data from the after-school program, we extracted three variables that measured learners' persistence on different levels. A cluster analysis based on those variables identified three learning patterns.

Cluster 1: High Persistence, Low Switch

The students in this cluster worked persistently on over 60% of the topics they attempted. Specifically, they attempted 31% of the tasks eight or more times. Within the ALEKS system, the problem type within a single topic/task is very similar, often with only the values of the problem changing. While this provides an opportunity for repeated attempts on a problem that targets a very specific skill, it is possible that students become bored and disengage. Despite the potential for becoming bored due to the lack of problem type variety, students in Cluster 1 did not readily switch topics after several failed attempts, suggesting high tenacity. However, persistence did not seem to facilitate effective learning, because there was no difference between this cluster and others in learning. In Beck and Gong's study (2013), they found learners wasted a large amount of time getting stuck, and were not able to master skills in Intelligent Tutoring Systems. They named this phenomenon "wheel-spinning", which refers to a car stuck in mud or snow with its wheels spinning fast but not going anywhere. It is possible that a certain amount of persistence behavior in Cluster 1 was actually wheel-spinning.

Cluster 2: Low Persistence, High Switch

In contrast with Cluster 1, the students in Cluster 2 were not very persistent. Generally, they frequently switched topics, and in most cases were not willing to attempt a task several times. Although students in Clusters 1 and 3 were more persistent than students in Cluster 2, a learning difference between the clusters was not observed. It seems that the topic shifting behavior does not necessarily equate to a student giving up. Students may switch from the topics that were too challenging in an effort to find topics that they were able to master.

Cluster 3: Moderate Persistence, Moderate Switch

The students in Cluster 3 switched on a medium portion of topics (23%) and worked with high effort on a comparatively low portion (18%) of topics. The students in this cluster were not as persistent as cluster 1, but were more persistent than cluster 2. They worked on the tasks with moderate persistence. It seems they were self-pacing in the self-regulated learning environment like ALEKS.

We used the analysis of covariance (ANCOVA) to examine the association between persistence and academic achievement and found that they were not correlated. This result is consistent with the hypothesis proposed by Stekel and Tobias (1977), who suggested that persistence and achievement are unrelated in an individual learning context. One thing to be mentioned is that the pretest and posttest used were TCAP5 and TCAP6, which were the standard tests for 5th graders and 6th graders. Therefore, they could cover different concepts and might not be well aligned. This is the limitation of this non-experimental study. Although learning gains were not found between pretest and posttest, the number of mastered topics were found to be different among clusters. The more persistent clusters--cluster 1 and cluster 3--mastered more medium and hard topics than the non-persistent cluster--cluster 2. This seems to indicate that persistent students put more effort on harder topics and non-persistent students just gave up. At the same time, the inconsistency of learning in ALEKS and standardized tests could be due to different reasons. First, students' learning gain might not be well reflected by TCAPs since TCAP5 and TCAP6 were not well aligned. Second, ALEKS and TCAPs might cover different topics, thus what students learned in ALEKS was not be well indicated by TCAPs. These issues need to be explored with further experimental study. Our analysis also found the most persistent cluster attempted more topics with moderate or high persistence without mastering them. This provides some insight as to why persistence did not make a difference in learning: the students were wheel-spinning (Beck & Gong, 2013). That is, even though students worked on topics persistently, they appear to be at an impasse that could not be resolved with more attempts, ultimately resulting in the student never mastering the topic. We explored two

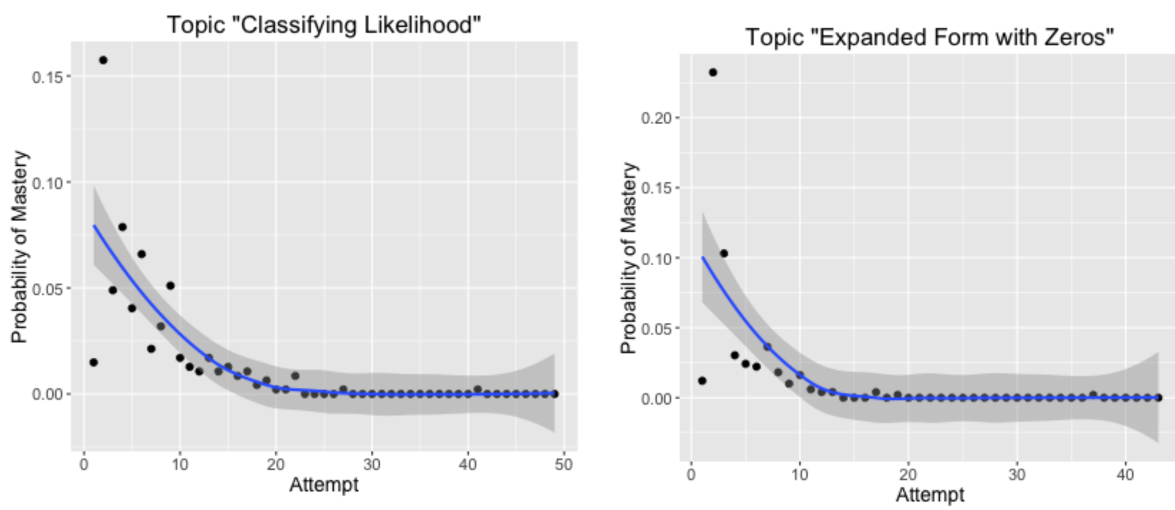

Figure 6. Mastery probability over attempts for topic "Classifying likelihood" and topic "Expanded form with zeros"

highly attempted topics in our data sets and found the probability of mastering those topics got close to zero after a certain number of attempts (as shown in Figure 6). This indicates the existence of wheel-spinning.

Chapter 5

Conclusion

While persistence was typically studied as the completion of online courses in online learning environment, this study took a different approach by examining persistence in specific tasks in ALEKS. Through clustering students' learning behaviors, three clusters with distinct behavior patterns were found. The comparison of students' academic achievement in three clusters did not show any significant difference between clusters. Due to the deficiency of our pretest and posttest, we could only suggest persistence on task might not be related to academic achievement in ALEKS. A further look at the possible reasons behind non-productive persistence suggested wheel-spinning might relate to ineffective learning. Although ALEKS has a system that can detect ineffective learning and provide feedback, like "Failed", to learners, the percentage of "Failed" was very low (i.e., 1%). In many cases, learners were struggling and wheel-spinning, but the system allowed the learners to continue making attempts without stopping them with a "Failed" indicator, or any other type of intervention. Therefore, we suggest some improvements of the mechanism to detect wheel-spinning behavior in ALEKS. When this behavior is detected, some interventions (e.g., suggesting the student to take a break, or review previous relevant content, etc.) could be done to reduce the negative effects of wheel-spinning. For instance, it was argued that when an individual has worked hard on a problem, a break might provide the individual an opportunity to recognize the learned knowledge unconsciously (Ma, 2009; Smith, 1995; Smith & Blankenship, 1989). This incubation effect was supported by some empirical studies (Medd & Houtz, 2002; Smith & Blankenship, 1989; Webster, Campbell & Jane, 2006). Therefore, with proper intervention such as an incubation break, we might be able to reduce unproductive persistence and the demotivation caused by it in ALEKS.

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Appendix

IRB Approval

THE UNIVERSITY OF MEMPHIS

Institutional Review Board

To:	Xiangen Hu and Scotty Craig Psychology
From:	Chair, Institutional Review Board for the Protection of Human Subjects
Subject:	Effective Applications of Intelligent Tutoring systems (ITS) in Improving the Skill Levels of Students with Deficiencies in Mathematics: An Efficacy Study (H09-25-01)
Approval Date:	August 5, 2009

This is to notify you of the board approval of the above referenced protocol. This project was reviewed in accordance with all applicable statutes and regulations as well as ethical principles.

Approval of this project is given with the following obligations:

1. At the end of one year from the approval date an approved renewal must be in effect to continue the project. If approval is not obtained, the human consent form is no longer valid and accrual of new subjects must stop.
2. When the project is finished or terminated, the attached form must be completed and sent to the board.
3. No change may be made in the approved protocol without board approval, except where necessary to eliminate apparent immediate hazards or threats to subjects. Such changes must be reported promptly to the board to obtain approval.
4. The stamped, approved human subjects consent form must be used. Photocopies of the form may be made.

This approval expires one year from the date above, and must be renewed prior to that date if the study is ongoing.

Approved

THE UNIVERSITY OF MEMPHIS
Institutional Review Board for the Protection of Human Subjects

Request for Modification/Addendum

Name Scotty Craig (Xiangen Hu) Phone: 901-283-7414 Fax ____________

Department: Psychology E-mail: scraig@memphis.edu

Faculty advisor (if student) ______________________________

IRB# H09-25-01 Date of most recent approval 8/4/2009

Please indicate your modification/addendum to your previously approved protocol and provide brief justification.

__X__ Additional instrument (attach copy)

_____Modification of instrument (attach copy)

_____Change in subject pool

_____ Number of subjects

_____ Age range of subjects

_____ Other

_____Change/addition of data collection site

_____Change to compensation

_____Change in recruitment methods

__X___ Advertisement/flyers (attach copy)

_____Other

Do the changes impact the consent form in any way? If yes, please attach the revised consent form. ________ Yes, consent attached ____X____ No

Details and Justification:
The research team will be contacting the parents of the children involved in our afterschool research program via a take home questionnaire sent home with the children and follow-up phone calls from the research team. Parents already gave us permission to contact by providing phone numbers and contact times on optional information sheets when they gave initial consent. This will be done as a form of respect for our enrolled participants to make sure they understand the program and the benefits it provides to their enrolled student(s). This will also serve as a recruitment/retention tool for the research team to encourage attendance after the break. The last purpose of the form

Approved by IRB ______________ Date 12/14/09

THE UNIVERSITY OF MEMPHIS

Institutional Review Board

To:	Scotty Craig Psychology
From:	Chair, Institutional Review Board for the Protection of Human Subjects
Subject:	**Effective Applications of Intelligent Tutoring systems (ITS) in Improving the Skill Levels of Students with Deficiencies in Mathematics: An Efficacy Study (H09-25-02)**
Approval Date:	**July 25, 2010**

This is to notify you of the board approval of the above referenced protocol. This project was reviewed in accordance with all applicable statutes and regulations as well as ethical principles.

Approval of this project is given with the following obligations:

1. At the end of one year from the approval date an approved renewal must be in effect to continue the project. If approval is not obtained, the human consent form is no longer valid and accrual of new subjects must stop.
2. When the project is finished or terminated, the attached form must be completed and sent to the board.
3. No change may be made in the approved protocol without board approval, except where necessary to eliminate apparent immediate hazards or threats to subjects. Such changes must be reported promptly to the board to obtain approval.
4. The stamped, approved human subjects consent form must be used. Photocopies of the form may be made.

This approval expires one year from the date above, and must be renewed prior to that date if the study is ongoing.

Approved

Cc:

THE UNIVERSITY OF MEMPHIS

Institutional Review Board

To:	Scotty D. Craig Institute for Intelligent Systems (IIS)
From:	Chair, Institutional Review Board For the Protection of Human Subjects irb@memphis.edu
Subject:	Effective Applications of Intelligent Tutoring Systems (ITS) in Improving the Skill Level of Students with Deficiencies in Mathematics: An Efficacy Study (061411-782) (Continuing Review for H09-25-02)
Approval Date:	July 1, 2011

This is to notify you of the board approval of the above referenced protocol. This project was reviewed in accordance with all applicable statuses and regulations as well as ethical principles.

Approval of this project is given with the following obligations:

1. At the end of one year from the approval date, an approved renewal must be in effect to continue the project. If approval is not obtained, the human consent form is no longer valid and accrual of new subjects must stop.
2. When the project is finished or terminated, the attached form must be completed and sent to the board.
3. No change may be made in the approved protocol without board approval, except where necessary to eliminate apparent immediate hazards or threats to subjects. Such changes must be reported promptly to the board to obtain approval.
4. The stamped, approved human subjects consent form must be used. Photocopies of the form may be made.

This approval expires one year from the date above, and must be renewed prior to that date if the study is ongoing.

____

Chair, Institutional Review Board
The University of Memphis

THE UNIVERSITY OF MEMPHIS

Institutional Review Board

To:	Xiangen Hu and Theresa Okwumabua Psychology
From:	Chair, Institutional Review Board For the Protection of Human Subjects irb@memphis.edu
Subject:	Effective applications of Intelligent Tutoring Systems (ITS) in Improving the Skill Levels of Students with Deficiencies in Mathematics: An Efficacy Study (#2378)
Approval Date:	October 16, 2012

This is to notify you of the board approval of the above referenced protocol. This project was reviewed at the expedited level in accordance with all applicable statuses and regulations as well as ethical principles.

Approval of this project is given with the following obligations:

1. At the end of one year from the approval date, an approved renewal must be in effect to continue the project. If approval is not obtained, the human consent form is no longer valid and accrual of new subjects must stop.
2. When the project is finished or terminated, the attached form must be completed and sent to the board.
3. No change may be made in the approved protocol without board approval, except where necessary to eliminate apparent immediate hazards or threats to subjects. Such changes must be reported promptly to the board to obtain approval.
4. The stamped, approved human subjects consent form must be used unless your consent is electronic. Electronic consents may not be used after the approval expires. Photocopies of the form may be made.

This approval expires one year from the date above, and must be renewed prior to that date if the study is ongoing.

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Chair, Institutional Review Board
The University of Memphis