Online Learning Persistence and Academic Achievement

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ABSTRACT
Student persistence in online learning environments has typically been studied at the macro-level (e.g., completion of an online course, number of academic terms completed, etc.). The current examines student persistence in an adaptive learning environment, ALEKS (Assessment and LEarning in Knowledge Spaces). Specifically, the study explores the relationship between students' academic achievement and their persistence during learning. By using archived data that included their math learning log data and performance on two standardized tests, we first explored student learning behavior patterns with regard to their persistence during learning. 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. No significant differences were observed between academic achievement and the different learning patterns. We interpret this result in addition to a preliminary exploration of topic mastery trends, to suggest that "wheel-spinning" behaviors coexist with persistence, and is ultimately not beneficial to learning.

Keywords
ALEKS, persistence, academic achievement

1. INTRODUCTION
Assessment of LEarning in Knowledge Space (ALEKS) is an online adaptive learning system built based on Knowledge Space Theory [8]. 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. 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 [3]. When a learner first use ALEKS, the system starts with an individualized initial assessment to find the student's knowledge state. The assessment usually consists of 20 to 30 problems (out of more than 600 problems). After the initial assessment, the student receives a report in a color-keyed pie chart (as shown in Fig. 1). Each "slice" of the pie chart corresponds to a particular area of the syllabus, and the darker shades of color indicating how much the student has mastered in that area [1]. 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. After successfully solving problems covering the same topic, the system will determine a student's mastery of the topic and the add the topic to the student's knowledge pie, and the student can then move onto a new topic [2].

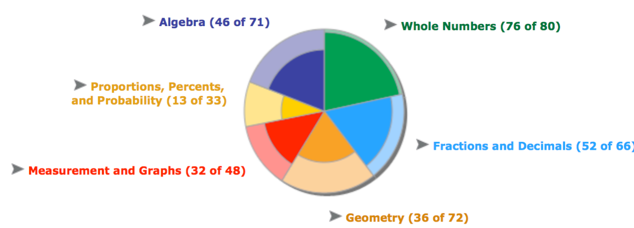


Figure 1: ALEKS knowledge pie showing number of concepts learner has learned and needs to learn

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 [6, 9, 12, 13, 16, 19]. These studies generally measured ALEKS students' learning gains or academic achievements; however, none of them looked at students' learning process, or online learning behaviors. In this study, we explored students' offline learning outcomes and online learning behavior patterns, and investigated whether persistence was associated with academic achievement in an individualized online learning environment. We further examined students' wheel-spinning behaviors [5] in order to understand the association.

2. RELATED WORK
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. 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" [15]. According to Rovai, persistence is the behavior of continuing action despite the

presence of obstacles [22]. 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 [7] found mastery goals and performance approach goals were positive predictors of persistence; Vansteenkiste et al. [24] found intrinsic motivation improved student persistence; Multon et al. [18] 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 [18], 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 [4, 7, 27].

In the context of online learning environment, persistence was usually defined as the completion of an online course, or an antonym of attrition [10, 14, 20, 22]. 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 [10, 14]. Persistence was mainly explored as a dependent variable affected by psychological and social factors, such as self-motivation, engagement, economic support, etc. [14]. Persistence was also investigated as a consequence correlated with online behaviors such as participation, discussion, etc. [17, 21].

Despite various studies on persistence in learning, persistence was rarely studied as a predictive factor. Stekel and Tobias [23] 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.* [7] 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 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. Therefore, we wonder whether persistence is unrelated to academic achievement in the individualized learning environment like ALEKS.

3. METHODS

3.1 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 one-hour sessions every week, for twenty-five 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. 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 another problem to work on. If the learner hits the "Explain" button, a worked example of that problem will be provided (as shown in Fig. 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.

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.

3.2 DATA PROCESS

The log file used in this study contains 366 students' 330,319 lines of online learning sequence. 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. We named the variables "Attempt", "Time" and "Master". Pearson product-moment correlation coefficient indicated that "Attempt" and "Time" 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 Fig. 2). Therefore, "Attempts" was chosen to measure student's effort on task. Next, we created three variables as measures of persistence and dummy coded them. They were "High persistence", "Moderate persistence" and "Switch". While "High persistence" and "Moderate persistence" were used to describe different levels of persistent learning behaviors, "Switch" was used to describe non-persistent behaviors when a student gave up a topic quickly and switched to a new topic before mastery. For a topic, if its log-

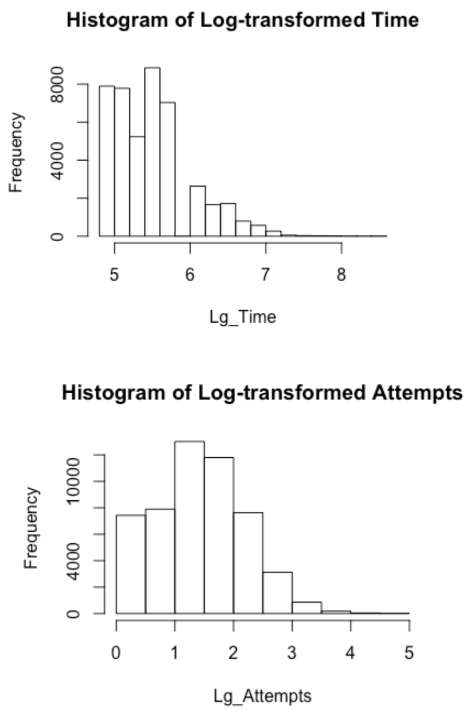


Figure 2: Distribution of log-transformed attempts and log-transformed time on each topic

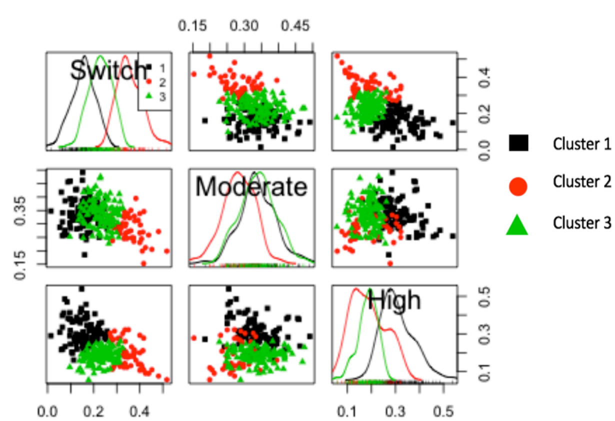
transformed attempts were in the fourth quartile of the distribution, "High persistence" was coded 1, otherwise it was coded 0. If its log-transformed attempts fell into the second or third quartile of the distribution, "Moderate persistence" was coded as 1, otherwise it was coded 0. For "Switch", both attempts and the result were taken into account. If a topic's log-transformed attempts was in the first quartile of the distribution, and the topic was not mastered, "switch" was coded 1, otherwise it was coded 0. After the new variables were created and coded, the 51,982 rows of data were aggregated to student level by averaging the persistence variables, and we got 366 observations. After second 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 attempted with some type of behaviors. If the total number of topics attempted by the were too small, it did not necessarily imply certain behavior patterns, even if the percentage for that behavior was high. Therefore, we decided to screen the students who only attempted a small number of topics. Based on the distribution of topics attempted by each student, the students whose attempted number of topics fell within the first quantile (Topics<=61) were screened from further analysis. There were 275 observations after screening.

After data process, we conducted cluster analysis to explore students' persistence learning patterns. We performed analysis of covariance to compare academic achievements of students from different groups to explore the association between online behavior and academic achievement. We also conducted analysis of variance to compare the mastery topics between groups to better understand the association.

4. RESULTS

4.1 CLUSTER ANALYSIS

There is no strictly defined sample size for cluster analysis. According to the suggestion of Formann [11], the minimal sample size should be no less than 2^{k} cases (k = number of variables), preferably $5*2^{k}$. The study examined the clustering of 275 observations across three variables, which fell comfortably within the accepted range. Ward's [25] 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 [26]. Examination of scree plot 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 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 Fig. 3. The scales are the percentage of topics students attempted with a specific behavior. 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 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 1.

Figure 3: Scatterplot matrices of three-level persistence of three clusters

Cluster 1: High persistence, low switch

Cluster 1 (i.e. the black cluster in Fig. 3) 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 1: 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 (σ=0.05)	0.36 (σ=0.05)	0.23 (σ=0.05)
Moderate persistence	0.34 (σ=0.05)	0.28 (σ=0 .05)	0.34 (σ=0.05)
High persistence	0.31 (σ=0.07)	0.19 (σ=0.07)	0.18 (σ=0.04)
TCAP5	46.72 (σ=18.25)	39.37 (σ=17.60)	47.28 (σ=17.23)
TCAP6	43.23 (σ=20.89)	32.69 (σ=18.44)	40.49 (σ=21.63)

Cluster 2: Low persistence, high switch

Cluster 2 (i.e. the red cluster in Fig. 3) 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 Fig. 3) 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.

4.2 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.

4.3 ANALYSIS OF VARIANCE (ANOVA) AND POST HOC TESTS

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

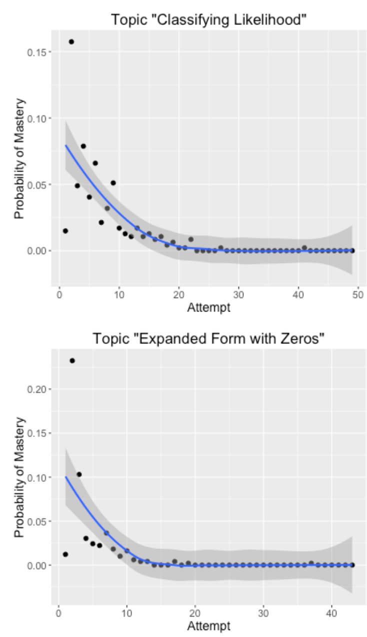


Figure 4: Mastery probability over attempts for topic "Classifying likelihood" and topic "Expanded form with zeros"

higher than both Cluster 2 and Cluster 3 in unmastered topics with both moderate and high persistence. This provides some insight as to why persistence did not make a difference in learning: the students were wheel-spinning [5]. We explored two 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 Fig. 4). This indicates the existence of wheel-spinning.

Another 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 cluster one and three mastered significantly more medium and hard topics than cluster two, but there was no statistically significant difference between cluster one and three. The means and standard deviations of the number of topics mastered by each cluster are shown in table 2.

Table 2: Means and standard deviations of the number of topics mastered by each cluster

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

5. DISCUSSION AND CONCLUSION

In previous research, student persistence has only been measured by macro-level data (e.g., completion of an entire course). This study took a different approach by examining persistence at a more micro-level; specifically, we looked at student persistence within specific tasks in the ALEKS learning system. We were able to extract three distinct clusters of persistence related student behaviors through cluster analysis. The students in the high persistence cluster put medium to high effort in most of the topics they attempted, and they rarely switched to a new topic before mastery. The students in the moderate persistence cluster put medium effort in most topics they attempted and they did not easily give up topics before mastery. The students in the low persistence cluster frequently switched to new topics before mastery, often giving up tasks after one or two attempts. The comparison of students' academic achievement in the three clusters did not reveal any significant difference. This result is consistent with the hypothesis proposed by Stekel and Tobias [23], who suggested that persistence and achievement are unrelated within individual learning contexts. Although learning gains were not different between clusters in standardized tests, the mastery of topics was found to be different. The more persistent clusters--cluster one and cluster three-- mastered more medium and hard topics than the non-persistent cluster--cluster two. This suggests persistence was associated with learning in ALEKS, especially for more difficult topics. The inconsistency between learning gain in ALEKS and TCAPs might be related to different topics covered in ALEKS and TCAPs.

It is worth noting that the pretest and posttest assessments present a limitation to the current analysis. The TCAP5 and TCAP6 were used as pretest and posttest measures, and may cover different concepts that are not well aligned. However, a further look at the possible reasons behind non-productive persistence suggested wheel-spinning might relate to ineffective learning. That is, even though students were persistently working on a single topic, they appeared to be at an impasse. These impasses were not resolved with more attempts, which ultimately resulted in the student never mastering the topic. 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 did not stop them with a "Failed" indicator, or any other type of intervention. Therefore, we suggest ALEKS to improve the mechanism to detect wheel-spinning and provide intervention in a timely manner.

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