Use of Intelligent Tutor in Post-Secondary Mathematics Educationi the United Arab Emirates

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ABSTRACT
The purpose of this paper is to determine potential identifiers of students' academic success in foundation mathematics course from the data logs of the intelligent tutor Assessment for Learning using Knowledge Spaces (ALEKS). A cross-sectional study design was used. A sample of 152 records, which accounts to approximately 60% of the population, was extracted from the data-logs of the intelligent tutor, ALEKS. Two-step clustering, correlation and regression analysis, Chi-square analysis and ANOVA tests were applied to address the research questions. The data-logs of ALEKS include information about number of topics practiced and number of topics mastered by each student. A derived attribute, which is the ratio of *number of topics mastered* to *number of topics practiced* is found to be a predictor of final marks in the foundation mathematics course. This variable is represented by the name *mtop*. Cluster classification based on this derived attribute resulted into three groups of students for which the mean values of the variable *mtop* are 0.80, 0.66 and 0.53 respectively. A moderately strong, positive and significant correlation was found between *mtop* and the final exam marks.

Keywords-cluster analysis, intelligent tutor, learning analytics, ALEKS

INTRODUCTION
It has been reported that many students spend a greater period of time in early years of the higher education especially in remedial or foundation programs; they spend more than expected without achieving the program requirements (Nasser, 2012). As Hansen et al (2006) explain, that secondary schools prepare students for university requirements but do less in preparing them to achieve at the level that universities require. Significantly, English language appears to be a difficult subject as most universities use that medium of instruction to teach science and non science subjects. Many students in the Gulf countries have not achieved a level of competency to enable them to successfully operate in English as a language of instruction and learning.

Many programs, techniques, and methods are in place to support foundation year students in their learning in higher education among them is continuous assessments and review which are probably one of the key ingredients to improve student learning strategies to be used for enriching their learning experience as it has the cognitive as well as the motivational purpose (Ritter, Anderson, Koedinger & Corbett, 2007). Timely feedback in assessments fills the gaps between the actual learning and expected learning outcomes (Chappuis, 2014). Formative assessment with feedback is particularly significant when students are uncertain about what is expected of them and when they need instructional guidance about how to move ahead (Nguyen, Hsieh & Allen, 2006; Wood & Wood, 1996). One claim is that the process by which students are monitored during instruction can help teachers provide timely feedback on students' actual learning.

While formative assessments or continuous assessments followed by feedback can be used periodically to assess students' learning, it may not be feasible or practical to incorporate in large class sizes, (Chappuis, 2014). The first years in higher education, a great deal of stress is placed on the instructor to carry out continuous assessments, or formative assessments and provide timely feedback. More lately the use computer-based assessment systems known as intelligent tutoring are widely used in secondary schools and higher education. These systems are web-based and designed to run on multiple devices such as laptops, iPads and mobile gadgets. They can be used to conduct frequent formative assessments with appropriate and timely feedback to minimize the gap between actual learning and expected learning (Narciss & Huth, 2004). It also engages students in authentic learning opportunities and can increase student participation and motivation in the learning process (Miller, 2009).

A key feature of these software systems is their ability to record and store every learning activity occurring when a student interacts with the system. The data gathered for every user can be analyzed providing the "learning profiles" for each student or at the aggregate level. A learning profile is useful to understand students' study habits and their progress (Kotsiantis, Tselios, Filippidi & Komis, 2013). Learning profiles can be detected by applying methods of *Learning Analytics* in which system-generated large data logs are analyzed in order to understand students' learning activities (Siemens & Long, 2011). The data generated support instructors to assess where the students are and where to go forward.

LITERATURE REVIEW

Computer based assessments

In class, the instructor can engage students in student-centered activities in the classroom through intelligent tutors. Students can access such systems online at any time or anywhere, for which they are expected to develop self-regulatory approaches to succeed and use the technologies available to them in and outside the classroom (Aleven, Roll, McLaren, Koedinger, 2010; Nicol, 2006; Nguyen, Hsieh & Allen, 2006). Web-based intelligent tutoring systems allow students to practice, to have control over their learning and manage their time and interaction with peers and instructors (McArthur & Stasz, 1990). Also the use of online computer based assessments, have several advantages over paper based assessments (Aleven, Roll, McLaren & Koedinger, 2010; Balacheff & Kaput, 1996; Hagerty & Smith, 2005), they provide access to any number of students anytime and anywhere through any type of computer, such as a laptop, tablet or a smart phone. They provide a wider range of assessment techniques than the paper based assessments, for example, inclusion of graphics and multimedia. Students can provide their responses in various formats, such as drawing graphs on a digital screen, locating number positions on a number line by clicking on the webpage. The most significant aspect of computer based assessments is that individualized feedback is given instantly. More importantly, the software applications can generate questions randomly from a large bank of questions and different versions of assessments produced to tailor different levels of learning outcomes and practice questions required for mastering a topic (Shute & Underwood, 2006). Moreover, such web-based software can foster student-centered learning by engaging students in meaningful learning activities and can increase students' engagement in learning (Chen et al, 2008; Chen, Yunus, Ali & Bakar, 2008; Nguyen, Hsieh & Allen, 2006; Schneider, Egan & Julian, 2013).

Intelligent tutors

Generally, a computer tutor or intelligent tutor establishes task-related goals and guides the learner toward the goal. An expert tutor is capable of designing learning tasks to ensure that the student persists on the task and gains some new knowledge, the student when interacting with the computer tutor may heavily rely on the system to work out a problem as an act of educational transference (Thelwall, 2000). While early computer-based learning was based on behaviorist learning theories that each application is taught as a separate learning objectives, into modules with separate objectives that are linked in such a way that the outcomes in one module can be used as an input into another. However more recent advances in cognitive sciences recommend adapting the constructivist learning theory and emphasize that "true" understanding as connected and generalizable knowledge wholes (Ritter, Anderson, Koedinger & Corbett, 2007). According to constructivist learning paradigm, a student could cultivate independent and self-directed learning and higher ordered thinking. Researchers as Chen, Yunus, Ali & Bakar (2008) and McArthur & Stasz (1990) have shown that computer-based or web-based assessments had positive effects on students' mathematical learning processes especially where problems required analytical and critical approaches for solving them. In mathematics immediate correction and feedback can generally have substantial real-time benefits to students as it gives them an opportunity to analyze the problem and readjust, reorganize, restate, and recalculate the problem work and move to higher levels of the taxonomy of educational objectives.

The current and emerging technologies, such as *intelligent tutors*, which are supported by artificial intelligence techniques have an advantage compared to other information technologies (Chen, Yunus, Ali & Bakar 2008; Chen et al, 2008; McArthur & Stasz, 1990; McGatha, & Bush, 2013). The *intelligent tutors* have the ability to integrate more than one medium, provide authentic and concurrent learning activities and provide academic-content based support to a large student body. As reported in (Stiggins, 2001; VanLehn, 2011) human tutoring has an effect size of d = 2.0 relative to classroom teaching without tutoring. This effect is known as the 'two sigma gain'. Developers of intelligent tutors work towards achieving the same effect as human tutors by incorporating multidimensional tutoring with appropriate feedback and scaffolding techniques based on the knowledge of the subject and the knowledge of student's state of learning (Kao & Lehman, 1997; Stiggins, 2001). Intelligent tutors' development is based on combining theories of cognitive science and techniques of artificial intelligence (Anderson, Boyle, Corbett & Lewis, 1990; Ritter, Anderson, Koedinger & Corbett, 2007;

McGatha & Bush, 2013; Miller, 2009). The intelligent tutors can provide interactive and personalized learning environment for students allowing them to study and learn individually (Hagerty & Smith, 2005).

Some intelligent tutoring system, such as *Cognitive tutor*, allows students to write solutions procedurally as if they were solving it on paper. The system gives feedback on each step as well as for the overall solution (Ritter, Anderson, Koedinger & Corbett, 2007) whereas, intelligent tutors like ALKES (Assessment for Learning using Knowledge Spaces), provides feedback only on the final answer. Cognitive tutors are appropriate for novice learners where every step is supported through feedback, use of systems like ALEKS is appropriate in higher education where students are expected to develop the ability to follow through problem-solving procedures with minimal support.

One of the prominent theoretical frameworks underlie the development of intelligent tutoring systems, is the framework of *knowledge space theory*. The knowledge space theory is applied to make the learner agile to learning. Tutoring systems, such as ALEKS, is built on the foundations of knowledge space theory that can gauge the level of student's understanding and can detect the correctness of student's next response on the basis of current response. ALEKS provides learning goals, scaffolding support for learning and allows for formative and continuous assessments and feedback.

At the core of the analytic engine is the concept of two fringes. One fringe which consists of all topics that *What a Student Can do* and the second fringe consists of all topics that the student is *Ready to do or Learn*. Refer to Table 1 for illustration.

Table 1: Two states of student's learning (excerpt only)

What H00298326 Can Do as of 09/15/2014	What H00298326 Is Ready to Learn as of 09/15/2014
Place Value, Expanded Form, and Numeral Translation	Exponents and Order of Operations
Numeral translation: Problem type 1	Writing expressions using exponents

ALEKS is user friendly and interactive. A student can choose any topic available from the list of 'Ready to Learn Topics.' A question is presented on that topic by the system, a student can request an explanation and if a student can respond to the problem correctly, positive reinforcement is prompted on the system. If the student can answer three more similar questions correctly, then the system allows the user to terminate the task by prompting the option of 'Done.' If a student is confident about the mastery of this topic then, they can click on the button 'Done,' and the topic is added to the list of 'what a student can do.' If a student cannot answer three to four consecutive questions correctly, then the system does not present questions from the same topic but suggests that the student can try another topic. ALEKS has the ability to create individualized sequence of topics based on the student's background knowledge and level of cognitive development but the instructions provided by ALEKS are static and same for all students irrespective of their individual learning styles. It does not provide instructions in different multi-media format, such as audio or video, but allows instructor to upload presentations and video files customized for students.

ALEKS sets two types of in-built and individualized assessments known by the *progress test* and *comprehensive test*. These assessments include questions from the two sets, the first, a set of topics mastered by the student and the set of topics which the student is ready to learn. Progress tests are administered by the system based on the topics mastered and time spent by the student, whereas comprehensive tests must be assigned by the instructor. The purpose of the progress test is to ensure that students can retain and recall his or her learning. Thus by diagnosing student's current state of knowledge, the software can provide scaffolding exercises and/or problems that help the student progress gradually. Each student can learn at her own pace and monitor her own progress. Inclusion of ALEKS in the foundation mathematics curriculum is aligned with the strategic decision of ministry of higher education in the United Arab Emirates (UAE) to basically integrate computer-based technologies in the educational processes.

Learning Analytics

Learning analytics focus on deriving information which can reveal how students use the intelligent tutoring systems and identify potential "identifiers" of academic achievement. (Desmarais & Baker, 2012; Holden, Sottilare, Goldberg & Brawner, 2012; Kotsiantis, Tselios, Filippidi & Komis, 2013; Libbrecht, Rebholz, Herding, Müller & Tscheulin, 2012). Application of methods of learning analytics can be a powerful means to inform and support learners, teachers and their institutions to better understand and predict individualized learning needs and performance (Greller & Drachsler, 2012; Siemens & Long, 2011, Tempelaar, 2014). There are specific student attributes when analyzing learning patterns, such attributes include time – spent on a topic, engagement with it and other system dispositional elements as skills and computer agility (Siemens & Long, 2011). Such system specific attributes are taken into account for analyzing students' learning patterns or their engagement in learning, but in some cases new attributes are derived to gain deeper understanding of determinants of students' learning (Antonenko, Toy & Niederhauser, 2012). Learning analytics attributes can be derived by combining the information about the number of topics practiced, time spent on learning and number of topics mastered. This analysis could provide information about whether a student can learn from the instructional queues and feedback provided by the software and utility for mastering the course content.

The system-specific attributes generated by ALEKS may not provide accurate information about student's learning efforts as the system cannot indicate the idle time, when students login to the system and do not attempt to respond. In addition, the time taken to master a topic is not signified as students are encouraged to learn at their own pace. It is worth investigating how to detect from such large data logs, information about students who are able to master a topic by studying independently.

We calculated the ratio of the two variables *number of topics mastered* and *number of topics practiced*, represented by the variable *mtop* (which is an abbreviation of *mastered-to-practiced)* which can be used as a construct of the extent of which the student has the ability to learn independently. The aim of this research is to examine whether *mtop* is a predictor of student's assessment in a course.

Course Structure

In the context of the UAE not too long ago, the ministry of higher education of the UAE took a decision to supply tablets to foundation year students in all federal higher education institutions. This decision was taken to address the strategy to develop technologically advanced environments to support learning in higher education (Gitsaky, Robby, Hamdan & Ben-Chabane, 2013). The supply of tablets to the foundation year students as the first year experience was perceived as an impetus for students to "ride" the information age and stay abreast of the technological advancement in higher education in preparation for the workplace (Nguyen, Hsieh & Allen, 2006; Yorke & Longden, 2004).

Two foundation courses covering basic arithmetic, algebra, geometry and statistics are delivered using the ALEKS software used tablets. Students use their tablets (iPads) to access this program. The software provides explanation and practice problems on each topic. Students are expected to master all topics as per their learning pace. Upon registering into the course on ALEKS, the software gives each student an initial assessment and detects their prior knowledge about the subject. This score is denoted by the variable Initial Assessment (IA). As the student interacts with the software and progresses towards the completion of all topics, the software maintains a record of progress and the status of mastery of the course is displayed in the form of a Pie chart as shown in Figure 1.

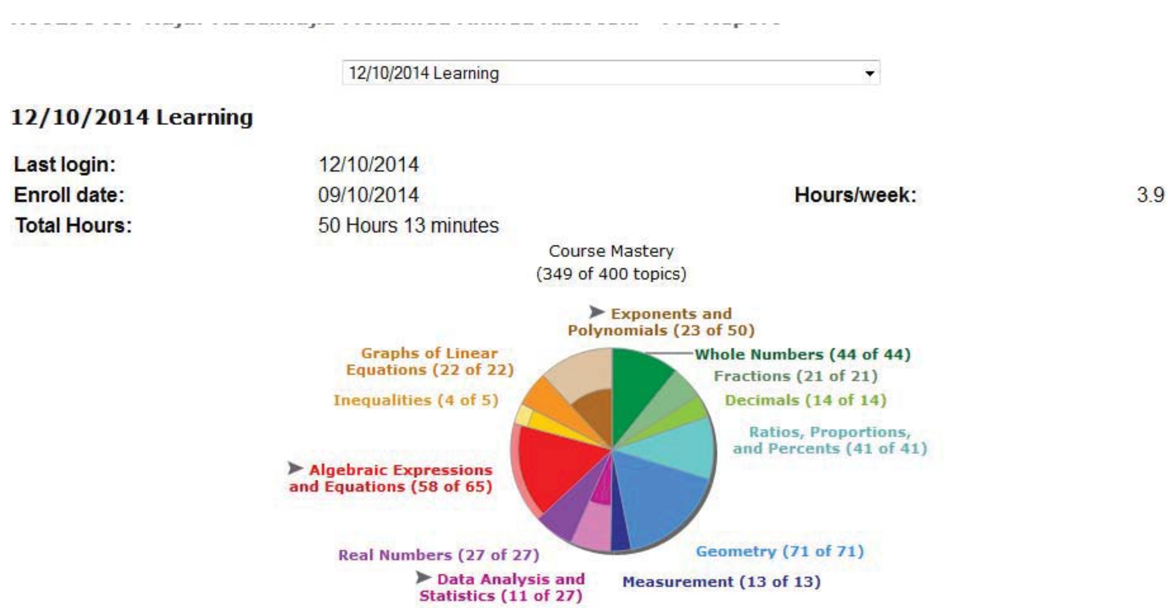

Figure 1: Pie-chart showing learning status of a student on ALEKS

In terms of course grade distribution through ALEKS, 40% weighting is assigned to completion of all topics, which works as the formative assessment. Students are expected to master these topics outside the regular class time. 60% weighting is given to in-class quizzes and the final exam which form the summative assessment component is denoted by FE in the rest of the paper. The assessments are created by teachers but graded by the software. Students can review their own answers after the examinations are graded, but the software does not provide a detailed feedback on their answers. The software only indicates whether the answer is correct or incorrect. In case of incorrect answers, the system does not provide an explanation. It only provides the expected correct answer.

There is also a summative assessment, which is a comprehensive test generated by ALEKS, and is based on what the student has mastered. This assessment component is denoted by CT in the rest of this paper. These tests are conducted in classroom under controlled conditions. After each test, the software indicates which topics are retained by the student and which are not. In these tests unlike the formative assessments, the software does not provide feedback on student's performance in the comprehensive test, neither teacher can see student's solutions nor the student can see their own answers and know the mistake; hence a student has to re-learn the topic that is dropped after each comprehensive test.

Regular course runs over 16 weeks but students who complete at least 85% of the topics after each comprehensive test are given an opportunity of exiting the course earlier than those who do not. The software allows teachers to set individual or group classwork, homework, quizzes and worksheets.

METHODS

Data was gathered from a cumulative report generated from a 20-weeks data which included the following information: time spent in ALEKS in each week, number of topics practiced each week and number of topics mastered each week. The excerpt of the data file used for analysis is given below and each variable is described subsequently.

Table 2: Excerpt of the data file

EPL (English Language proficiency)	Number of progress tests Ptests	IA	CT	FE	EE (early exit)	WT-1 (Time spent in week - 1 in min)	WM-1 (Topics mastered in week -1)	WP-1 (Topics practiced in week-1)	*mtop*-1 (Ratio of WM-1 /WP-1)	WT-1 (Time spent in week - 1 in min)	WM- 2 (Topics mastered in week - 2)	WP-2 (Topics practiced in week-2)	*mtop*-1 (Ratio of WM-1 /WP-1)
3	6	36	83	71	Yes	237	22	25	0.88	432	24	37	0.65
3	5	27	61	61	No	38	4	4	1.00	189	19	21	0.90
3	4	28	50	32	No	48	0	0	0.00	251	25	34	0.74
3	7	17	65	60	No	288	26	27	0.96	1334	126	152	0.83
3	3	23	62	60	No	72	5	5	1.00	365	30	31	0.97

IA=Initial assessment , CT= Comprehensive test, FE=Final Exam; WM-1: Topics mastered in week-1; WP1-Topics practiced in week-1,*mtop*-1: Ratio of WM-1/WP-1 WM-2: Topics mastered in week-2; WP2-Topics practiced in week-2, *mtop*-2: Ratio of WM-1/WP-1. …..

The data file also included the following variables: student's score in the initial assessment (IA), total number of topics mastered by the student after the comprehensive test (CT), student's marks in the final exam (FE), and number of progress tests taken by the student (Ptest) and whether the student passed the course or not in less than 12 weeks. If a student passes the course in less than 12 weeks, then the values assigned attribute to variable EE is "Yes."   For other students who do not pass in less than 12 weeks, the assigned attribute to this variable is "No." The system administers progress tests based on the number of topics completed by a student. The number of progress tests attempted is different for each student as the pace of their learning is different. In the data file, the variable *Ptest* denotes the number of progress tests taken by a student. The ratio of the two variables of topics mastered to topics practiced is represented by the variable *mtop* for each week and is used as a measure of ability to learn independently. The mean value of this variable *mtop* over 20 weeks was calculated. Refer to the Table 2 given above.

This research aims to assess the relation between student's ability to work independently through ALEKS and student's final marks in the course. The research aims are:
(1) To explore learning profiles of students based on similar learning patterns.
(2) To investigate the following research questions:
Does the ability to work individually effect students' marks in the coursework and in the final exam?
Does the proficiency in English affect the ability to study individually?

Data Analysis
The data file consisted of 152 records from five sections of Basic Mathematics and Pre-Algebra taken at a 4-year technical college in the UAE. The students were in the foundation year, and candidates enter regular degree programs upon completion of English and Mathematics courses.

In the first stage of the analysis the Shapiro-Wilk test of normality was applied to test the normality of the variable *mtop.* The result shows that value of the statistic is 0.99 and p-value is 0.142. Since the p-value is higher than 0.05, it implies that the variable *mtop* is normally distributed and hence parametric tests are applicable.

Cluster analysis
In order to determine which groups of students have similar learning profiles, a cluster analysis can be applied (Antonenko, Toy & Niederhauser, 2012; Cohen, Manion, and Morrison, 2011). Two-step clustering method is applied where variables are continuous and the number of clusters is not known apriori (Field, 2009). Students are classified into clusters based on the mean value of the ratio of topics mastered to topics practiced (*mtop)*. The clustering created three different profiles based on the value of the variable *mtop*. The software detected three clusters by applying the Log-likelihood method. Based on these cluster profiles, it is observed that the students in the cluster number one had the highest value for the variable *mtop*, which means on an average they mastered 80% of the topics out of the topics that they practiced, whereas students in the cluster two and cluster three mastered only 66% and 53% of topics, respectively. One-way ANOVA test was applied to test if these clusters were independent of each other. The results of the ANOVA test showed that the mean value of *mtop* was statistically different for each cluster (F=10.26, p-value=0.000), which confirms that the three clusters are independent of each other.
Table 3 presents the cluster distribution and the mean and standard deviation of the clusters.

Table 3: Cluster profiles

Cluster number	Mean (*mtop*)	S.D. (*mtop*)	Number of students
1 (high)	0.80	0.05	32
2 (Medium)	0.66	0.05	61
3 (Low)	0.53	0.03	59

Effect of mtop on early completion of the course. As described in the section above, students were given an opportunity to pass the course in less than 12 weeks if they mastered 85% of topics by studying independently. A total of 34 students out of 152 passed the course within 12 weeks. Out of those 34 students, the 44% belonged to the cluster two which means a high percent of students who passed the course early, were able to master 67% of the topics they practiced. Whereas 35% students belonged to the cluster one, which means they were able to master 80% of the topics they practiced. A total of seven students in this cluster three passed the course in less than 12 weeks, which means they were able to master only 53% of the topics they practiced.

Table 4: Cross-table showing number of students who passed the course early in each cluster

			Two-Step Cluster Number			
			1(high)	2 (medium)	3 (low)	Total
Early exit	No	Count	20	46	52	118
		% within early exit	16.9%	39.0%	44.1%	100.0%
	Yes	Count	12	15	7	34

	% within early exit	35.3%	44.1%	20.6%	100.0%
Total	Count	32	61	59	152
	% within early exit	21.1%	40.1%	38.8%	100.0%

Whereas though students in the cluster one, had a high score for *mtop,* 20 students from this cluster did not pass the course early. Refer to Table 4 for further detail.
A Chi-square test analysis was performed to test if the number of students who passed the course in less than 12 weeks is the same for each cluster. The distribution of students was statistically different. (Chi-square statistic= 8.42, p=0.017). It can be concluded that there is evidence to support our claim that the variable *mtop* predicts academic achievement, as the early exit from the course is based on a high score in the coursework as well as in the final exam.

Effect of number of progress tests attempted on the final grades.
The variable *Ptest* was analyzed to determine if the progress tests administered by the software are supporting students' academic achievement. The descriptive statistics of this variable revealed that the minimum number of progress tests taken by students was zero, the maximum number was 13. The average number of progress tests taken by students in clusters one, two and three are 3.47, 4.21 and 3.83 respectively. The average number of progress tests was not statistically different when compared among the three clusters (F=0.378, p=0.48). It can be concluded that the number of progress tests taken by students is not associated with value of the indicator *mtop*. There was no statistical evidence to claim that students in different clusters attempted different number of progress tests and whether the number of progress tests had any impact on their learning efforts.

Correlation and ANOVA test.
Further ANOVA test and correlation analysis were carried out to test whether *mtop* can be considered as a predictor of the final exam (FE) and the coursework (CT). The ANOVA test results showed that the mean value of coursework marks and final exam marks are different for all three cluster groups. The difference was found to be statistically significant at 0.05 level for CT, F(2, 151)= 4.89, p=0.01 and FE, F(2, 151)=4.28, p=0.019, consequently a statistical difference among the three groups.

Also, a moderately strong positive and statistically significant correlation was found between the value of mean *mtop* and the marks in the final exam (r=0.41, n=152, p=0.000). From the results of ANOVA test and correlation analysis, higher value of *mtop* indicates higher marks in FE and CT. It can be concluded that the ability to study individually is one of the predictors of student's marks in the coursework and in the final exam.

Regression analysis
Since the correlation between *mtop* and FE is significant, further linear regression analysis was done. The unstandardized coefficient for the variable was 69.2, p=0.00 and the constant term is determined as 17.9, p=0.03.

The value of R^2 is 0.166, which indicates the 16% of the changes in FE are explained by the changes in *mtop*.
This implies that there are other predictors which should be explored further.

Effect of English language proficiency. Out of 152 students, 41 students had a moderate level of English language proficiency whereas 111 students had low level of English language proficiency with M=0.63 and SD=0.1 compared to those in level 4 who had a mean of M=0.67 and SD=0.12.

Parametric independent samples t-test was applied to test the hypothesis for research question 3. The output of the independent samples t-test (t-value= -2.165 and p-value=0.034) indicates that the mean value of *mtop* was statistically different between the two groups based on their language proficiency level. These results indicate that students' English Language proficiency affects their ability to learn independently. For the current research, students' marks in English were not available for further analysis.

DISCUSSION

On average, students mastered 64% of the topics they practiced. Students in cluster 1 have a higher rate of mastering topics whereas students in cluster 3 had a lower rate of mastering topics. Refer to the Figure 2 for further detail.

The high score for *mtop* can be attributed to the regularity in studying whereas the low score of mastering can be due to a lack of time and effort spent at the task. Although some students may be spending sufficient time still they may not achieve the expected mastery and such students will have a low score for *mtop*. Instructors can monitor students' progress periodically and identify students whose score for *mtop* is less than 0.6. These students may need encouragement, motivation as well as additional support to understand a topic.

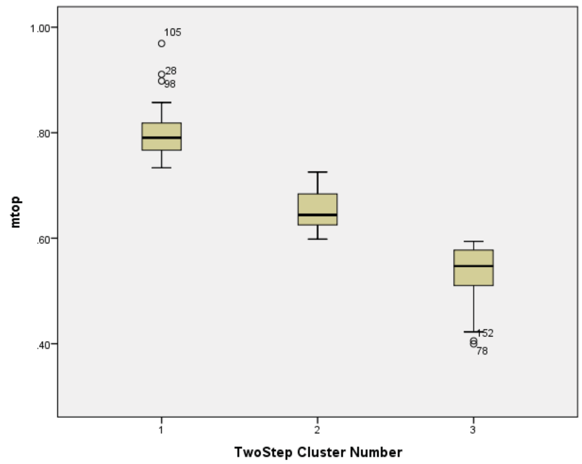

Figure 2: Box-plots for each cluster.

Further investigation was done to examine if the distribution of students with different language proficiency is uniform across the three clusters.

Table 5: English language proficiency and cluster membership

English level proficiency			Two-Step Cluster Number			Total
			1(high)	2(medium)	3(Low)	
Level	Low	Count	18	46	47	111
		% within Level	16.2%	41.4%	42.3%	100.0%
	Moderate	Count	14	15	12	41
		% within Level	34.1%	36.6%	29.3%	100.0%
Total		Count	32	61	59	152
		% within Level	21.1%	40.1%	38.8%	100.0%

One of the factors affecting students' ability to learn independently is poor language skills. As shown on Table 5, only 16% of students with low level English proficiency had a high score for *mtop* and they belonged to the cluster one and 42% had a low score for *mtop* belonged to cluster 3.

Another factor affecting the ability to study individually is poor technology skills. Poor technology skills result into the under-utilization of the features of ALEKS which is likely to result out of inability to understand gaps in what a student knows and what is expected of them. One pertinent theoretical framework is Vygotsky's concept of zone of proximal development. It refers to the gap between 'what a student can do alone' and 'what he can achieve with the support from an expert'. The interactions between the expert and the student are termed as 'tutorial interactions' and the expert is termed as the 'tutor'. The gap between the expert and novice can close through scaffolding techniques embedded in the ALEKS software that provide strategies to implement goals of constructivist learning paradigm, building on student experience and prior knowledge (Azevedo & Hadwin, 2005; Hohenwarter, Hohenwarter, Kreis & Lavicza, 2008).

The most important feature of ALEKS is that it designs a sequence of activities appropriate for each student and allows the student to learn at his or her own pace. As a result, it builds confidence in the student to solve problems independently. From the findings we can see that the complete potential of ALEKS is utilized, if students follow the learning paths suggested by ALEKS. Currently ALEKS interface is not providing clear instructions about how to achieve this and further development may be needed to enhance this aspect of the software.

According to the knowledge space theory, a student is not able to solve problems unless he or she has mastered the pre-requisite topics. The limitation in the application is there are no clear instructions presented on the home screen of the system. Students often misinterpret this representation as not to complete those topics. This can be avoided with an improved representation and menu friendly system, in which the student can see the list of all topics without a hyperlink to their detailed explanation.

Occasional progress tests are administered by ALEKS to detect where students are and generally to formatively assess where they can move forward. After each of these formative assessments benchmarks or progress tests, the previous learning score is adjusted. This mechanism provides accurate and up to date model of student's learning progress. Students tend to avoid the automatic progress tests and they request teachers to cancel it. It may be due to these reasons: the system does not provide details and feedback about the solution submitted during automatic progress tests and they have to relearn all topics which are not retained in the progress test. These tests may affect the confidence of students because some questions are taken from the list of topics which a student have not yet mastered, however, but the system finds that the student is ready to learn. Weaker students fail to answer these questions which result in decreasing their previous achievement score. In order to remove these barriers in learning independently, students should be given more training about how to use the system. Also quizzes and homework assignments on ALEKS can be set as formative assessments as the system provides feedback on these assessments unlike the progress tests.

CONCLUSION

In this paper, we established the ratio of topics mastered to topics practiced *(mtop)* as an indicator of student's ability to study individually. This indicator was further applied for classifying students. This classification formed three groups of students for which the mean *mtop* were 0.80, 0.66 and 0.53 respectively. A strong positive and significant correlation was found between the *mtop* and final exam marks and between *mtop* and the coursework marks, which indicates that *mtop* can be a predictor of student's final marks in the ALEKS based course.

Based on the evaluation of the system, we found that ALEKS can measure student's attainment of factual and procedural knowledge, but it fails to measure meta-cognitive aspects, because neither ALEKS shows the different strategies to solve these problems nor students could show the strategies used for problem solving in order to develop metacognitive abilities. Thus, the ALEKS based coursework can be supplemented by project assignments but may require instructional feedback from the instructor. The expectation is that the performance effect size of such type of sophisticated intelligent tutors is almost equal to that of expert human tutor (VanLehn , 2011),

LIMITATION AND FUTURE DIRECTION

Though this is a quantitative study and the results are significant, some limitations of this study must be considered before generalizing the results. It should be noted that the participants in this study are all female students studying English as their second language and this is their first year of using English as the medium of instructions. Male students or students with higher proficiency in English may have different ways of learning using the tutor. Considering also that learning may be different for a different type of intelligent tutor, results can be generalized only on similar population and similar type of intelligent tutor.

The application of intelligent tutors may not provide the same result to all students. There are other factors, such as learning style, efforts, cognitive agility, the affective state of learner and ability to learn using the technology, which may have different achievements. Though effectiveness of intelligent tutors has been confirmed by many researchers, some researchers claim that if students believe a computer can't help them learn (even though they do actually learn), then they have a high probability of disliking the system. They may believe that they cannot learn from the tool and may become less motivated to use the tool for learning (Jackson, Graesser & McNamara, 2009). In continuation of this study, other non-cognitive factors such as students' learning styles; their attitude towards technology and towards mathematics will be analyzed along cognitive and educational elements related achievement to understand the impact of these factors on students' learning experience.

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