Effect of Intelligent Tutoring on Teaching and Learning Mathematics: The case of use of Ignite the Learning System in selected primary schools in Kenya

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Abstract

Research show that Intelligent Tutoring Systems (ITS) are beneficial for teaching and learning. The systems can help learners acquire skills and knowledge faster than those who only use traditional approaches such as learning from text books or chalk and talk. Moreover, there is a shortage of expert teachers particularly in rural areas in most developing countries including Kenya. To address this issue, an Intelligent Tutoring System that teaches mathematics to elementary school learners in Kenya was developed. Ignite the Learning is an Intelligent Tutoring System developed by Elimuplus team to teach mathematics in elementary schools. The system is a constraints-based tutor and provides worked-out examples, error flagging and hints feedback messages. A study was conducted to evaluate effectiveness of the system in public and private schools in Kenya. The results showed that both groups in public and private schools learned from Ignite the learning.

Keywords: *Worked examples, problem solving, intelligent tutoring systems, digital technologies, ignite the learning.*

Introduction

In most developing countries, shortage of teachers and tutors is an issue that affect government and private run schools however, the problem is more acute in public rural schools especially in developing countries. When the number of learners to teachers per class increase, Intelligent Tutoring Systems become very useful tools. This is because the amount of human tutor's time dedicated to each learner become inversely proportional to the number of learners. On the other hand, computer based Intelligent Tutors Systems (ITS) simultaneously interacts with a large number of learners at the same time. These systems could be beneficial in developing countries where there is lack of teaching resources to enhance the quality of teaching. This study suggests some solutions to address this limitation in Kenya by developing an Intelligent Tutoring System named "Ignite the Learning (IL)" that teaches mathematics to learners at elementary school level that could rolled to other subjects and education levels. This learning system is a constraint-based tutor that requires learners to solve problems which could be applicable to competency based curriculum frame work (GoK, Education, Task force report, 2012). In constraint-based learning system , the teacher , the learner and the domain models are represented in form of constraints (Ohlsson, 1992). During this study experiments were conducted in one private school and in a public school to explore the efficiency of the system in two different environments. In Kenya most public schools often have more learners per classroom compared to private schools. For example, some public schools especially in urban areas may have more than hundred learners per class. Therefore, it was hypothesized that Intelligent Tutoring Systems could be more useful in teaching and learning in public schools than private schools. On the other hand, learners in public schools are more likely to have less experience working with digital technologies compared to more resource endowed learners in some private schools. Therefore, it was interesting find out whether there were more benefits from Intelligent Tutoring System when learners were not well exposed to digital technologies.

The goal of this study was to demonstrate that the system promotes learning as students work with the Ignite the Learning application. Moreover, in Kenya, learners in private schools may have more learning resources than those in public schools, hence the assumption that learners in the public schools would have greater learning gains from ITS than learners in the private schools. Learners in public schools may have less exposure to digital technologies than those in most private schools. This lack of exposure to digital technology among learners in public schools was anticipated to slow down their performance in use of ITS.

Literature review

Computer based learning provide enhanced educational support to learners and teachers. Most of the earlier work on computer-based learning systems focused on pedagogies and behaviour to enable the systems to act like expert human teachers (Carbonell, 1970). Computer-Based teaching and Computer Aided Instruction (CAI) were the earliest systems that were used to help learners in acquiring knowledge and skills, but those systems were inflexible. These systems did not give individualized feedback based on the learner's responses and the learners were presented with the same study materials. Later, some computer based systems allowed learners to get any content they wished by using a navigation control, while others forced learners to follow the prescribed order of the learning material. The navigation control allowed the learners to skip some materials and work on the concepts they preferred to learn. Therefore, this study was grounded on three overlapping types of theoretical e-learning systems: Computer Based Teaching (CBT), Adaptive hypermedia and Intelligent Tutoring System (ITS) (Mathews, 2012). The relationship among the three types is shown in Figure 1.

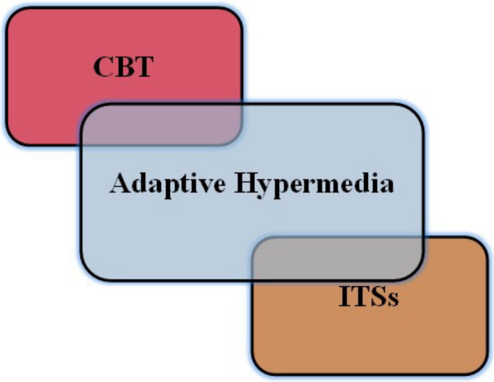

Figure 1. The relationship between the three types of e-learning systems (Mathews, 2012)

Virtual learning environments of today are Computer Based Teaching systems and the most popular of these are Learning Management Systems (LMSs). LMSs allow branching, in which students can access the domain content in any order. LMSs also allow for forums, quizzes and links to web pages and attachments. While learners work with the system, a LMS collects the information in the background. Therefore, teachers can observe the performance of the learners. In the LMS, teachers organize the content and the system does not have any understanding of the content or the structure of the domain. A few Computer Based teaching systems are adaptive, such as Moodle (Modular Object-Oriented Dynamic Learning Environment)[1]. Moodle has a *lesson module*[2] which has two types of pages: content pages and question pages. Question pages are the branches of the content pages, but the learner's answers to a question can take the learner to an entirely different page. Therefore, students may experience different paths through the knowledge base, depending on their answers (Brandl, 2005).

Adaptive hypermedia systems adapt in some way to course content, the learner or both. An adaptive system might control the navigation by disabling a link when the student has not learnt the required materials (Brusilovsky, 2001). Navigation based adaptation can be implemented in different ways: *direct guidance* for example a 'next' or 'continue' button; *adaptive sorting*, in which the system sorts the links of learning material according to the user model; *adaptive hiding*, which hides certain irrelevant or distracting links; and *link annotation*, in which the system provides more information by adding colour or icons to a link (Brusilovsky, 2001).

An Intelligent Tutoring System (ITS) is an instructional procedure that recognizes the learner's behavioural patterns and provides a suitable response to those patterns (Beck and Stern, 1996). Therefore, understanding learners' differences is often crucial. Different ITS components make teaching decisions and maintain a record for each student. ITSs lead to significant learning (Graesser et al., 2003; Suraweera and Mitrovic, 2004; Suraweera and Mitrovic, 2002) and even improve understanding similar to those resulting from expert human tutors (VanLehn, 2011).

Researchers have developed ITSs for numerous domains using a variety of approaches, for example in algebra (Koedinger *et. al.*, 1997), geometry (Koedinger and Anderson, 1993), object-oriented software design using class diagrams (Baghaei *et .al.*, 2007), Structured Query Language (SQL) and Cash Flow Statements (Kern et .al., 2014)). Some ITSs have been developed for individual learning, while some are for collaborative learning. They provide a problem solving environment for learners to practice and solve questions while the system guide learners towards correct answers.

There are several approaches for developing ITSs such as Model Tracing (MT) (Anderson *et al.*, 1985), Constraint-Based Modelling (CBM) (Mitrovic et al., 2001; Mitrovic et al., 2007) and Example tracing (Aleven, McLaren, Sewall, and Koedinger, 2009). These three methods are used for developing tutors with problem-solving environments.

Model Tracing is based on the Adaptive Character of Thought-Rational (ACT-R) theory of cognition (Anderson, 1996). In the theory, a difference is made between procedural and declarative

[1] http://moodle.org (February, 2017)

[2] http://docs.moodle.org/22/en/Lesson_module (February,2017)

knowledge. For example, all the algebra laws that a student has studied about in the text book are declarative knowledge. Using declarative knowledge, the student knows how to apply the knowledge for solving a problem. Production rules specify which procedural knowledge is applied to solve a problem. Thus, a production rule is the relationship between a situation, a goal and an action. The action takes the person from the current situation to the goal.

$$Situation, Goal \rightarrow Action$$

Therefore, the production rules can represent the domain knowledge in the domain knowledge model. An example of the production rules is shown as follows:

$$If\ the\ goal\ is\ to\ solve\ A + B = C\ for\ B$$
$$Then\ rewrite\ the\ equation\ as\ B = C\text{-}A$$

In MT systems, a number of paths for solving a problem are defined and any undefined path is considered as an error. However, incorrect production rules can be modelled for frequent mistakes. These incorrect production rules are also known as the bug library (Mitrovic et al., 2003; VanLehn et al., 2005). The bug library represents the student's misunderstandings. The MT approach has been used to develop successful ITSs for a variety of domains, including algebra (Koedinger el al., 1997), geometry (Koedinger and Anderson, 1993) and programming in Lisp (Anderson and Reiser, 1985).

Constraint Based Tutor is based on the theory of learning from performance errors (Ohlsson, 1996). Ohlsson (1992) suggests that domain knowledge can be represented as a number of constraints. A constraint consists of an ordered pair of $\{C_r, C_s\}$. C_r is the relevance condition and C_s is the satisfaction condition. If, in a scenario, a relevance condition applies, then the satisfaction condition must also be met. For instance, if a driver is driving in Kenya then she/he must be driving on the left side of the street. When the relevance condition is met and the satisfaction condition has not been met, the constraint is violated. In a constraint-based tutor, the student solution is checked against all constraints in the domain model. If no constraint is violated then the solution is correct; otherwise, the system can provide the student with feedback messages corresponding to each violated constraint. The student model keeps a list of satisfied and violated constraints for all submissions; thus, a constraint-based tutor can track the usage of constraints over time.

In a constraint-based tutor, the student is not restricted to following a specific problem-solving procedure. Therefore, it is possible for the system to support multiple correct solutions. In such systems, it is easy to add new problems (Mitrovic, 2012).

Structured Query Language – (SQL)Tutor is the first constraint-based tutor (Mitrovic, 1998; Mitrovic and Ohlsson, 1999). CBM tutors have also been implemented to teach a wide range of domains, including Java programming (Holland *et al*., 2009), object-oriented software design using UML class diagrams (Baghaei et al., 2007), capital investment (Mitrovic et al., 2008), electronics (Billingsley et al., 2004), English language learning (Menzel, 2006), discrete mathematics (Billingsley and Robinson, 2005), Cash Flow Statement (Kern et al., 2014), Newtonian physics (Mills and Dalgarno, 2007) and thermodynamics (Mitrovic et al., 2011).

Example-tracing approach unlike model-tracing and constraint-based methods evaluates student behaviour by comparing it against generalised examples of problem-solving behaviour. Example-tracing tutors provide step-by-step feedback by interpreting a student's problem-solving behaviour with respect to a behaviour graph. The behaviour graph is the generalised solution for the given problem (Aleven et al., 2009). Example-tracing approach has been used for developing different ITSs in different domains such as Stoichiometry (McLaren et al., 2006).

Although many ITSs have been designed, only a few are in commercial use. SQL tutor is one of these ITSs, developed in the Intelligent Computer Tutoring Group (ICTG) at the University of

Canterbury, to teach Structured Query Language (SQL) (Mitrovic, 1998; 2003). SQL tutor is a constraints based tutor with more than 700 constraints shaping its domain model. The tutor provides a problem solving environment for higher education learner and guides them through the solution. Currently SQL tutor contains more than 300 questions covering six clauses in a SQL statements: select, from, where, having by, group by and order by.

Intelligent Cash Flow Statement (iCFS) is another example of constraints based tutors that is aimed to teach Cash Flow Statement (CFS) to higher education students (Kern et al., 2014). The system contains more than 1000 constraints and more than 40 scenarios for students to solve. In average it takes one hour for students to prepare a Cash Flow Statement for each scenario in iCFS. The problems are designed in 5 levels of difficulty and cover both direct and indirect approaches to prepare cash flow statements.

Cognitive Tutor is another example of ITSs that is aimed to teach Algebra (Koedinger el al., 1997). The commercialised name of the software is named MATHia [3] (also known as Carnegie Learning Algebra 1) that is developed to teach learners mathematis. The tutor cover Grade 6 to Grade 12 based on United States curriculum. The software uses model tracing approach and helps students learn mathemtics by solving problems.

Problem solving is the main learning strategy in Intelligent Tutor system. It provides the learner with with a problem-solving strategy with problems of different complexities and guide them to correct answers. This guidance can be via either positive or negative feedback. Positive feedback is the tutor's response to correct learner's solutions and negative feedback is for incorrect solutions. Learners gain more skills from worked out examples than in unsupported problem solving learning activities. Sweller et al. (2011) explained that worked example effect underlying the Cognitive Load Theory (CLT). Sweller (2006) identified three different loads for the working memory: intrinsic, extraneous and germane load. Intrinsic load is caused by the nature and difficulty of the learning task; as the problem become more complex, its intrinsic load also become higher. Extraneous load is caused by information which is not related to learning like noise in the class or an unrelated joke during the teaching. In contrast to the extraneous load, germane load is caused by information which is related to learning materials. Najar and Mitrovic (2013) explained that mixing worked examples and problems is beneficial for learning. Najar, Mitrovic and McLaren (2016), incorporated problem-solving with worked out examples in SQL-Tutor. They proposed an adaptive strategy that selected learning activities for learners from worked examples. The decision is made based on learners' performance in their last problem-solving activities. The performance is measured by calculating assistance score that describes how much help learners received while solving the last problem (Shareghi Najar and Mitrovic, 2014).

Background of the study: Ignite the learning and Intelligent Tutor System

In this study experiments were performed on learning process in elementary mathematics using Ignite the Learning intelligent system. This a constraint-based tutor that teaches Mathematics. Ignite the Learning contains more than 10000 problems from 700 concepts with more than 3000 constraints.

Developing constraints is the most time demanding and important procedure during development phase. Each constraints requires 60 minutes in average to prepare, test and add to the system. Two computer programming experts, three expert teachers and five data entry staff spent more than 3200 hours work over 18-month to develop constraints and add them into the system. The system has two types of constraints: syntax constraints and semantic constraints. In the syntax type, constraints check

[3] http://www.carnegielearning.com/products/software-platform/mathia-learning-software (May, 2017)

students' solution format and symbols; for example, it checks for a specific symbol such as '%' in the student solution if it is required in the ideal answer. Semantic constraints check conceptual mistakes; for instance, a semantic constraint checks if students incorrectly calculated perimeter of a rectangle than the area of rectangle.

Questions in Ignite the Learning are uniquely developed for this system by more 10 Kenyan expert teachers. The teachers have many years of experience working with Kenyan curriculum and questions were designed in a way that can be easily provided to all students in Kenya. The teachers designed questions in different complexity levels from Level 1 to Level 10 (low to high). Note, concepts may have less than ten complexity levels. Each question in average takes thirty minutes to design. Teachers provided a problem statement, an ideal solution, a procedural explanation and a worked-out example per question. The teachers spent more than 5000 hours work over two years to deliver questions and five data entry staffs and two graphic designers spent eight months to enter the questions into the system.

The system can be used as a complement to traditional teaching and learning mathematics. It assumes that the learner has already acquired some knowledge through class activities. The teacher or the tutor provides numerous problem-solving opportunities. Ignite the Learning covers mathematic concepts from Grade 1 to Grade 8 based on elementary curriculum. Each grade contains three semesters and the system allows parents or teachers register students in one of the semesters. For example, parents or schools can register students for semester two in Grade 7. Then, once students log in for the first time, the system gives a pre-test to evaluate students' knowledge about concepts in semester 2 of Grade 7.

Questions in the pre-test were randomly selected. Figure 2 shows a screenshot of the pre-test. Learners do not receive feedback about their submitted solutions during the pre-test.

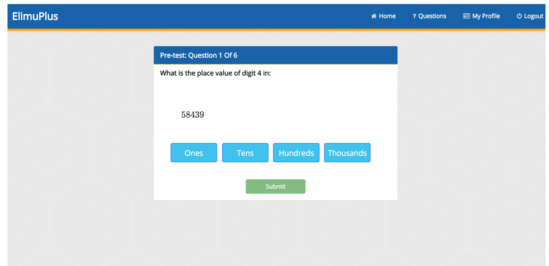

Figure 2. Screenshot of a pre test page

Once the pre-test is completed, the system selects a concept and a question for students to solve. Figure 3 shows a screenshot of problem solving page. Then the system shows a question with simplest complexity for the learner to solve. When the learners solve a problem with a low assistance score, the system increases the complexity of problem until the score indicates that the students have mastered the concept. Assistance score is a method of measuring student's performance in solving a problem by considering levels of feedback messages that students see (Najar et al., 2016).

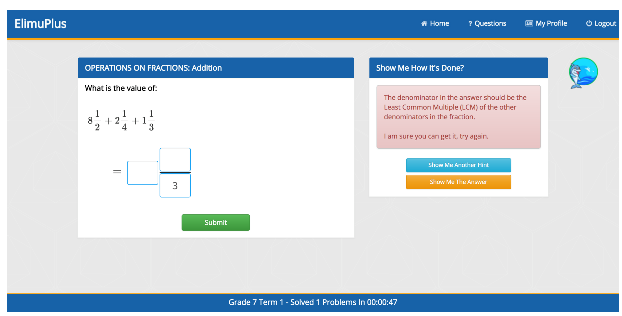

Figure 3. Screenshot of problem solving page

Ignite the learning covers 700 concepts from Math curriculum. This includes the overlapping concepts; for example, 'addition of fractions' is a concept that is included in Grade 5 Semester 1, Grade 6 Semester 1 and Grade 7 Semester 1. System provides different levels of feedback messages in each of these terms meaning that students in higher grade generally receive less help from the system. Moreover, for a similar concept, average complexity of questions in higher grades is higher than average complexity of questions in lower grade.

The system provides different levels of feedback messages: simple (positive/negative) feedback, error flag, hint, work-out example, complete solution and procedural explanation. Positive or negative feedback has the lowest level of assistance and its message inform learners whether their answer was correct or not. An error flag message advises students about the error they made or draw learners attention to what exactly the problem statement is requesting. More explanation is provided when a hint-type feedback is requested. Each problem had an attached worked-out example that is provided once learners request for worked out example. Work-out examples demonstrate a procedural explanation on how to solve a similar question. Complete solutions reveal final answers without explaining solutions. However, when students see complete solutions, the system give the learners an option to see the procedural explanation of solutions. The complete solution only is available between 30 to 60 seconds after the learners see a problem and submits two incorrect solutions. The waiting time is randomly selected. Figure 4 shows a procedural explanation of a question from a concept about *square root of fractions*.

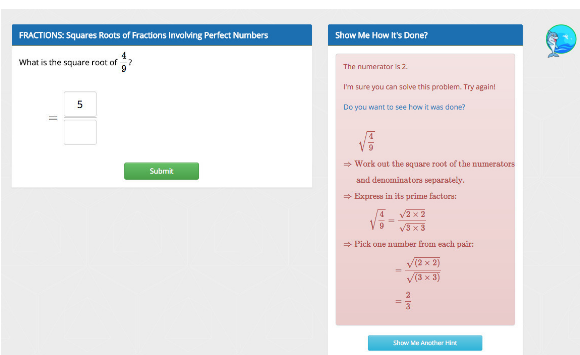

Figure 4. Screenshot of a complete solution and procedural explanation

The learners sit a post-test when they become advanced in all concepts of a semester. The post-test questions, similar to pre-test, are randomly selected from test questions of the term. This is the way the system measures the learners' gain since the pre-test provided appropriate reports for the teachers and parents who would like to monitor learner's performance. Parents and teachers had an option of encouraging the learners to repeat the semester in the system if their post-test was below a threshold. The threshold was defined by teachers or parents.

Research Methodology

In order to evaluate the system three experiments were conducted in one public and two private schools in Nairobi county , Kenya. The participants were boys and girls studying in Grade 7 during semester 1. The purposively selected sample of target population consisted of 27 learners from The Green Garden School, 21 learners from Shepherds Junior School and 64 learners from Plainsview Primary School. The studies were conducted during the tenth-week of the school semester.

The learners had studied about six concepts beforehand and needed a practise in the computer laboratory. The list of mathematical concepts covered during this experiment included: Units Used in Measuring Length and their Conversions, Combined Operations on Decimals, Operations on Fractions (Addition), Combined Operation Involving Fractions, Combined Operation, Percentage Increase and Place Value. The concepts were selected by two teachers from each school. The learners did not receive any inducements for participating in the study, but were informed that working with the system would help them in enhancing their mathematical skills. They were made aware that they would have a pre-test followed by a few problems to solve with the help of the system. They were also informed that the experimental session would be ended by a post-test. Learners also had to complete a questionnaire before leaving the computer laboratory.

The study was conducted in a single, 60-minute session. At the beginning of the session, the students took a pre-test; containing six questions to solve for 10 minutes. Learners started the learning session after completing the pre-test. The system selected the best questions and concepts for students to solve based on students' performance in the pre-test. It was expected that selecting appropriate concepts for students to practice and providing worked example as one level of feedback messages would improve the learning time and also avoided expertise reversal effect (Kalyuga et al., 1998) .It also improved learning gains. Expertise reversal effect indicated that worked examples were more convenient in the early stages of learning while students could benefit more from problem solving in later stages (Salden et al., 2009). The learners had access to all levels of feedback messages mentioned in Section 3 while they solved mathematical problems. They were allowed to ask questions from teachers if they had difficulties working with the system.

The learners took a post-test for 10 minutes at the end of the session. Pre-test and post-test questions were designed and balanced by the expert teachers. Each test had six questions. After the post-test learners had to respond to a questionnaire which had five multiple choice questions with no time limitation.

Results

Due to a technical issue, most of the students in Green Garden School did not see the post-test; therefore, we excluded 27 students from Green Gardens School in the following analyses. One student from Shepherds Junior School and two students from Plainsview Primary School did not complete the post-test; therefore, we exclude their data. We calculated the average of scores in the pre-test and the post-test and the time students spent on the system (Table 1).

Table 1. Basic statistics for all the participants

Number of learners	82
Pre-test (%)	61 (28)
Post-test (%)	70 (26)
Learning time (min)	32 (14)

Table 2 presents some data about students in public (Pu) and private schools (Pr). As mentioned before Plainsview Primary School is a public school and Shepherds Junior School is a private school. A significance level of 0.05 was used for all analyses.

The t-test revealed a significant difference on the pre-test performance of the two groups ($p<0.01$); therefore, the groups were not comparable. That is, students in the private schools were more advanced in the use of computers than the students in the public school during the time of experiment. Even though both groups had covered all the experimental materials in the class, the pre-test revealed that learners in the private school have had better educational support by the school and their teachers compared to those in the public school. A clear reason for this is the large number of learners sitting in each classroom. In the private school we had only 21 learners in a class and in the public school there were more than 60 learners in a class. Because the two groups were not comparable, in the analyses, more focus on the system efficiency for the both groups were emphasized.

The paired t-tests show that learners in Pu and Pr condition improved significantly between the pre-test and the post-test. Learners in both groups spent similar time working with the system. The result shows that Ignite the Learning system significantly improved learners' mathematical knowledge in the both private and the public schools.

Table 2. Dependent variables for novices (^{N} Normalized)

	Pu	Pr
Number of students	62	20
Pre-test score (%)	56 (28)	78 (22)
Post-test score (%)	65 (26)	88 (19)
Improvement pre- to post-test	$p < .01$*, $t = -2.88$	$p = .04$*, $t = -2.26$
Learning gain ^{N}	0.12 (0.63)	0.30 (0.55)
Learning time (min)	32 (15)	32 (13)

The learners also rated cognitive load, complexity of the tasks and the efficiency of the system on the Likert scale from 1 to 5 (*low* to *high*). Table 3 shows the result. Question 1 measures cognitive load imposed by the system.

Question 2 measured how much the system was efficient in helping learners acquire mathematical skills. Learners indicated that the system was very helpful. Learners in private school indicated a significant higher score than public school learners ($p = 0.02$). This is perhaps because learners in private school had some experience working with other educational systems. Therefore, they had better viewpoint in such systems in helping them learn their courses.

In Question 3, learners indicated how easy it was for them to work with the system. The learners in the private school indicated a lower score than those in the public school ($p<0.01$). Learners in the public school had less exposure to computers and tablets than those in the public schools. Some learners in public schools were grabbing a mouse for the first in their life and some were struggling to log into the system. Therefore, a few minutes were spent before the experiment to teach Pu learners about the system and how to they could use it. This posed some cognitive load for Pu learners which could be the reason why they found the system less easy to work with compared to Pr group. Question 4, tested whether they would like to use the system again. Both groups indicated high scores for this question.

Table 3. Ease of Use of the system

		Pu	Pr
Question 1	How much effort did you put to solve the questions?	3.24 (1.13)	2.95 (1.50)
Question 2	How much do you think the system can help you to learn mathematics?	4.26 (0.77)	4.68 (0.47)
Question 3	How easy was it for you to work with the system?	2.68(1.11)	4.35 (0.67)
Question 4	How much did you like using the system?	4.81 (0.40)	4.8 (0.41)

Overall, the results show that ignite the Learning improved students' knowledge from the pre-test to the post-test. The system was effective for both public school learners and those in private school . The learners in private school found the system easier to work with compared to those in public school .

Discussion

The study show that ignite the learning is beneficial for learning. Both learners in public and private schools learnt from the system and indicated that they liked the system. The system is different from available systems in the market as it is focusing on Kenyan curriculum. The system summarizes all materials related in one term in a package; therefore, learners who register in the system receive a package of different materials from questions to solve and worked-out examples. The system is developed based on constraints based modeling approach while most of the commercialized ITSs for teaching math are based on model tracing approach. Therefore, adding questions in Ignite the learning as a constraints-based tutor is much easier than available model tracing tutors (Antonija Mitrovic et al., 2003).

Ignite the Learning has an authoring tool that allows teachers and administrators to create questions in the system. The system currently has more than 10000 problems from 700 concepts in elementary school level Mathematics. We believe that Ignite the learning is a suitable software for Kenyan learners as findings in this study show since the system is tailored to improve learners' knowledge considering available learning resources in schools and at homes.

Even though Ignite the Learning only covers math questions, the system is capable to be extended to other domains such as science, history and social studies . This migration requires minimum development time and most of the efforts is towards content generation by teachers.

Conclusions

Intelligent Tutoring Systems are beneficial for learning. The systems have been developed for different domains such as algebra, geometry, chemistry for lower grade students and Cash Flow

Statement for higher education learners. Generally, learners in private schools have more educational resources such as computer laboratories and online educational resources than those in public schools. Moreover, in Kenya, the number of learners per class in public and private schools is very different. Public schools have larger class size on average. This often affects learners' attention and reduces one to one teacher to learner interactions. ITS can reduce teachers work load by providing individualised learning environment for learners. This will afford teachers opportunities for one to one interactions with the learners who are struggling in learning process.

The results showed that both groups in public and private schools learned from Ignite the learning. The system imposed reasonable cognitive loads for both groups. The learners in public school had a little exposure to computers and tablets hence the system imposed extraneous load that is load that does not help learning and caused cognitive over load. Extraneous load is caused by information which is not related to learning for example too many elements in user interface. However, the results show that ignite the learning had appropriate simple design hence it does not impose high extraneous load Moreover, Ignite the learning provided worked-out examples as a level of feedback message. Since worked out examples impose less cognitive load than problem solving, this can be another reason why an appropriate cognitive load score was indicated by the learners.

Although there was no significant difference between the two public and private school groups in cognitive loads, students in the private school indicated that the system was easier for them to work with than the students in public school. The reason is because many students in public schools did not have any exposure to tablets or computers. Some learners in the public school worked with mouse and keyboard for the first time in their life and they had never logged in to a website. In future experiments learners will be asked about how familiar they are with computers. This will allow the study to have a better picture on this issue.

In this study, we initially had a control group, in which students were supposed to learn from a human tutor. Unfortunately, due to time constraints the teacher was not briefed appropriately and s/he solved pre-test and post-test questions during the learning session; therefore, we had to stop the session and exclude the data from all analysis. Lacking a control group in this analyses limited us to further conclusions from the results. We consider this as one of lessons we learnt during this experiment. Teachers may not be familiar with A/B testing approach; thus, a significant amount of time needs to be spent on training teachers to make sure that we will have comparable groups. Teachers should be notified that the system is designed to assist them in teaching and the experiment should not be taken to reflect teachers' individual performance

In this study we did not measure long term retentions between learners in public and private schools due to lack of resources. In future studies learners will be provided with more hardware and software in order to measure the direct effects of the system. Ignite the learning provided worked-out examples as feedback message. In future, the effects of Ignite the Learning for novices and advanced students will be investigated.

References

Aleven, V., McLaren, B. M., Sewall, J., & Koedinger, K. R. (2009). A New Paradigm for Intelligent Tutoring Systems: Example-Tracing Tutors. *Artificial Intelligence in Education*, *19*, 105–154.

Anderson, J. R. (1996). ACT: A simple theory of complex cognition. *American Psychologist*, *51*(4), 355–365.

Anderson, J. R., & Reiser, B. J. (1985). The LISP tutor. *Byte*, *10*(4), 159–175.

Baghaei, N., Mitrovic, A., & Irwin, W. (2007). Supporting collaborative learning and problem-solving in a constraint-based CSCL environment for UML class diagrams. *Computer-Supported Collaborative Learning*, *2*(2–3), 159–190.

Beck, J., & Stern, M. (1996). Applications of AI in Education. *Crossroads*, *3*, 11–15.

Billingsley, W., & Robinson, P. (2005). Towards an intelligent online textbook for discrete mathematics. In *Proceedings of Int. Conf. on Active Media Technology* (pp. 291–296).

Billingsley, W., Robinson, P., Ashdown, M., & Hanson, C. (2004). Intelligent tutoring and supervised problem solving in the browser. In *Proceedings of Int. Conf. on WWW/Internet* (pp. 806–810).

Brandl, K. (2005). Are you ready to "Moodle." *Language Learning & Technology*, *9*(2), 16–23.

Brusilovsky, P. (2001). Adaptive hypermedia. *User Modeling and User-Adapted Interaction*, *11*(1–2), 87–110.

Carbonell, J. R. (1970). AI in CAI: An artificial-intelligence approach to computer-assisted instruction. *IEEE Transactions on Man-Machine Systems*, *11*(4), 190–202.

Graesser, A. C., Jackson, G. T., Mathews, E. C., Mitchell, H. H., Olney, A., Ventura, M., … Group. (2003). Why/AutoTutor: A test of learning gains from a physics tutor with natural language dialog. In R. Alterman & D. Kirsh (Eds.), *Proceedings of the 25th Annual Conference of the Cognitive Science Society* (pp. 474–479). Cognitive Science Society.

Holland, J., Mitrovic, A., & Martin, B. (2009). J-LATTE: a Constraint-based Tutor for Java. In S. C. Kong, H. Ogata, H. C. Arnseth, C. K. K. Chan, T. Hirashima, F. Klett, … S. J. H. Yang (Eds.), *Proceedings of the 17th Int. Conf. on Computers in Education* (pp. 142–146). Hong Kong: Asia-Pacific Society for Computers in Education.

Kalyuga, S., Chandler, P., & Sweller, J. (1998). Levels of Expertise and Instructional Design. *Human Factors and Ergonomics Society*, *40*, 1–17.

Kern, T., McGuigan, N., Mitrovic, A., Najar, A. S., & Sin, S. (2014). iCFS: Developing Intelligent Tutoring Capacity in the Accounting Curriculum. *Learning in Higher Education*, *20*(3), 91–103.

Koedinger, K. R., & Anderson, J. R. (1993). Effective use of intelligent software in high school math classrooms. In *Proceedings of Int. Conf. on Artificial Intelligence in Education* (pp. 241–248). Charlottesville, VA: Association for the Advancement of Computing in Education.

Koedinger, K. R., Anderson, J. R., Hadley, W. H., Mark, M. A., & others. (1997). Intelligent tutoring goes to school in the big city. *Artificial Intelligence in Education*, *8*, 30–43.

Mathews, M. (2012). *A Framework for Multiple Adaptable Pedagogical Strategies in Intelligent Tutoring Systems*. University of Canterbury.

McLaren, B. M., Lim, S.-J., Gagnon, F., Yaron, D., & Koedinger, K. R. (2006). Studying the effects of personalized language and worked examples in the context of a web-based intelligent tutor. In M. Ikeda, K. D. Ashley, & T.-W. Chan (Eds.), *Proceedings of Int. Conf. on Intelligent Tutoring Systems* (pp. 318–328). Taiwan: Springer Berlin Heidelberg.

Menzel, W. (2006). Constraint-based modeling and ambiguity. *Artificial Intelligence in Education*, *16*(1), 29–63.

Mills, C., & Dalgarno, B. (2007). A conceptual model for game-based intelligent tutoring systems. In R. J. Atkinson, C. McBeath, S. K. A. Soong, & C. Cheers (Eds.), *Proceedings of Australasian Society for Computers in Learning in Tertiary Education* (pp. 692–702). Singapore: Centre for Educational Development, Nanyang Technological University.

Mitrovic, A. (1998). Experiences in implementing constraint-based modeling in SQL-Tutor. In B. Goettl, H. Halff, C. Redfield, & V. Shute (Eds.), *Proceedings of Int. Conf. on Intelligent Tutoring Systems* (pp. 414–423).

Mitrovic, A. (2003). An Intelligent SQL Tutor on the Web. *Artificial Intelligence in Education*, *13*(2–4), 173–197.

Mitrovic, A. (2012). Fifteen years of constraint-based tutors: what we have achieved and where we are going. *User Modeling and User-Adapted Interaction*, *22*(1–2), 39–72.

Mitrovic, A., Koedinger, K., & Martin, B. (2003). A Comparative Analysis of Cognitive Tutoring and Constraint-Based Modeling. In P. Brusilovsky, A. Corbett, & F. de Rosis (Eds.), *Proceedings of Int. Conf. User Modeling* (Vol. 2702, p. 147). Springer Berlin / Heidelberg.

Mitrovic, A., Martin, B., & Suraweera, P. (2007). Intelligent tutors for all: Constraint-based modeling methodology, systems and authoring. *IEEE Intelligent Systems*, *22*, 38–45.

Mitrovic, A., Mayo, M., Suraweera, P., & Martin, B. (2001). Constraint-Based Tutors: A Success Story. In L. Monostori, J. Vancza, & M. Ali (Eds.), *Proceedings of 14th Int. Conf. on Industrial and engineering applications of artificial intelligence and expert systems: engineering of intelligent systems* (pp. 931–940). Budapest, Hungary: Springer Berlin / Heidelberg.

Mitrovic, A., McGuigan, N., Martin, B., Suraweera, P., Milik, N., & Holland, J. (2008). Authoring constraint-based tutors in ASPIRE: A case study of a capital investment tutor. In *Proceedings of Int. Conf. on education multimedia, hypermedia and telecommunications* (pp. 4607–4616).

Mitrovic, A., & Ohlsson, S. (1999). Evaluation of a constraint-based tutor for a database language. *Artificial Intelligence in Education*, *10*(3–4), 238–256.

Mitrovic, A., Williamson, C., Bebbington, A., Mathews, M., Suraweera, P., Martin, B., … Holland, J. (2011). Thermo-Tutor: An intelligent tutoring system for thermodynamics. In *Proceedings of IEEE Global Engineering Education Conference* (pp. 378–385).

Najar, A. S., & Mitrovic, A. (2013). Examples and Tutored Problems: How can Self-Explanation Make a Difference to Learning? In H. C. Lane, K. Yacef, J. Mostow, & P. Pavlik (Eds.), *Proceedings of 16th Int. Conf. on Artificial Intelligence in Education* (Vol. 7926, pp. 339–348). Memphis, USA: Springer, Heidelberg.

Najar, A. S., Mitrovic, A., & McLaren, B. M. (2016). Learning with intelligent tutors and worked examples: selecting learning activities adaptively leads to better learning outcomes than a fixed curriculum. *User Modeling and User-Adapted Interaction*, *26*(5), 459–491.

Ohlsson, S. (1992). Constraint-based Modelling. *Artificial Intelligence in Education*, *3*, 429–447.

Ohlsson, S. (1996). Learning From Performance Errors. *Psychological Review*, *103*, *No. 2*, 241–262.

Salden, R. J. C. M., Aleven, V., Schwonke, R., & Renkl, A. (2009). The expertise reversal effect and worked examples in tutored problem solving. *Instructional Science*, *38*(3), 289–307.

Shareghi Najar, A., & Mitrovic, A. (2014). Examples and Tutored Problems: Is Alternating Examples and Problems the Best Instructional Strategy? *Research and Practice in Technology Enhanced Learning*, *9*(3). Retrieved from http://www.apsce.net/uploaded/filemanager/460cc33b-328c-410a-aee2-6ff68f3aebcc.pdf

Suraweera, P., & Mitrovic, A. (2002). KERMIT: a constraint-based tutor for database modeling. In S. A. Cerri, G. Gouarderes, & F. Paraguaçu (Eds.), *Proceedings of 6th Int. Conf. on Intelligent Tutoring Systems* (pp. 377–387). Biarritz, France.

Suraweera, P., & Mitrovic, A. (2004). An Intelligent Tutoring System for Entity Relationship Modelling. *Artificial Intelligence in Education*, *14*, 375–417.

Sweller, J. (2006). The worked example effect and human cognition. *Learning and Instruction*, *16*(2), 165–169.

Sweller, J., Ayres, P., & Kalyuga, S. (2011). *Cognitive load theory*. Springer.

VanLehn, K. (2011). The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems. *Educational Psychologist*, *46*(4), 197–221.

VanLehn, K., Lynch, C., Schulze, K., Shapiro, J. A., Shelby, R., Taylor, L., … Wintersgill, M. (2005). The Andes Physics Tutoring System : Lessons Learned. *Artificial Intelligence in Education*, *15*(3), 147–204.