An analysis of the application of intelligent tutoring systems on students' self-regulated learning development

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Structured Abstract

BACKGROUND

Intelligent tutoring systems (ITS) can provide one-to-one tutoring opportunities to every student at any time and in any place by applying artificial intelligence technologies to model students' learning progress and understand teachers' teaching strategies. As attractive as this may sound, the reality is that the potential of such an ITS has yet to be realized and in practice such systems have had only a limited impact on classrooms. One potential reason for the slow uptake of such a teaching approach is that students studying alone with an ITS require a higher level of self-regulated learning skills (SRL). If these skills aren't properly inculcated it is less likely that students will commit to long-term use of an ITS.

PURPOSE

Previous studies have reported that SRL skills have significant positive impacts on student's learning outcomes. Much of the research on applying ITS to improve student's SRL abilities has accumulated from 1998 to 2014. So far, however, there has been little discussion about the available options to measure and support SRL in these types of ITS, and the system's effectiveness on learner's academic performance.

DESIGN/METHOD

The study collected 53 empirical studies of designing, implementing and evaluating ITS – those ITS which not only teach domain knowledge but also foster a learner's SRL abilities. Meta-analysis was applied as the main research method in order to gain comprehensive insights into the ITS in this field.

RESULTS

Our analysis suggests that no ITS in this field had negative impact on students' learning outcomes. The results of this research support the idea that ITS is an effective teaching method to foster a student's SRL abilities, and that use of such an ITS has a small positive impact on student's learning outcomes.

CONCLUSIONS

The ITS evaluated here used learning analytics and collected event data to measure a learner's SRL progress, rather than using self-reported data, which might be common for traditional classroom instruction. The fundamental modes of scaffolding were prompts and feedback. Moreover, the timing of prompt's appearance (just-in-time or delayed), and the content of the feedback (context-sensitive or context-insensitive) had a significant influence on student's learning outcomes. The SRL mechanism could be embedded in an ITS from the initial design stage or be retro-fitted to an existing ITS as add-on agents afterwards. Most of these systems were model-tracing ITS and multi-agent systems. While most of the ITS in this field were designed for STEM (Science Technology Engineering and Mathematics) subjects, relatively little was found in the literature on ITS applied in Engineering education, and in particular in electrical engineering.

KEYWORDS

Intelligent tutoring systems; self-regulated learning; meta-analysis.

Introduction

A significant challenge for engineering education is adequate coverage of a rapidly increasing body of knowledge (BOK). Moreover, “massification” of education has led to many universities facing challenges arising from increasing student-instructor ratios. A growing diversity in academic preparedness compounds this problem. Intelligent tutoring system(s) (ITS) provide a potential solution. They can, in principle, provide customized instruction for every student by being adapted to a particular student's academic needs and learning styles (Ray & Barnett, 2009; VanLehn, 2011; Woolf, 2010). Thus every student using such an ITS can access one-to-one tutoring opportunities at any time and in any place.

As attractive as this may sound, the reality is that the potential of such an ITS has yet to be realized and in practice such systems have had only a limited impact on classrooms. One potential reason is that when some ITS teach complex STEM (Science Technology Engineering and Mathematics) topics and present complex information in a non-sequential order, they can lead to student cognitive overload. The other potential reason for the slow uptake of such a teaching approach is that students studying alone with an ITS require a higher level of self-regulated learning skills (SRL). If these skills are not properly inculcated it is less likely that students will commit to long-term use of an ITS. Furthermore, it is even less likely they will emerge from tertiary study well equipped for independent learning.

Much of the research on applying ITS to improve students' SRL abilities has accumulated from 1998 to 2014. This paper reports the analysis of 53 empirical studies of designing, implementing and evaluating ITS – those ITS which not only teach domain knowledge but also foster a learner’s SRL abilities. Because of the growing interest in this field a number of questions regarding the kind of ITS can now be addressed by a meta-analysis:

1. What models of self-regulated learning have been used to guide system design?
2. What options are available to measure the learners’ self-regulated learning skills?
3. What scaffolding approaches are used to foster learners’ self-regulated learning skills?
4. How effective are intelligent tutoring systems in improving students’ learning outcomes?
5. What are the features of such intelligent tutoring systems?

Background

Intelligent Tutoring System(s) (ITS)

ITS apply artificial intelligence technologies to model students’ learning progress and understand teachers’ teaching strategies, so that they can build a student-centered learning environment – an environment under the guidance of cognitive science (Woolf, 2010). Aleven and his colleagues (2010) determined that ITS helped students learn complex cognitive skills by providing step-by-step guidance. To do this, an ITS should have a well-designed user interface, provide adaptive prompts, give step-by-step feedback, and share the control of study with learners.

The classic framework of an ITS has four components (Woolf, 2010):

1. **Domain knowledge:** to teach new knowledge to students. An ITS should act as an expert in a specific domain. As a result they need to contain key knowledge points - such as concepts; the relationships among different concepts; operation procedures and required skills.
2. **Student knowledge**: the main benefit of ITS is that they can understand a particular learner’s characteristics, learning styles and a learner’s knowledge level and so can offer adaptive instructions/feedback. In order to do this, an ITS needs to record and analyze

student information, set up a student model and reason and predict a student's next step(s).

3. **Tutoring knowledge**: to act as a human tutor, an ITS should also include relevant teaching strategies. After analyzing a student's knowledge, the ITS can then determine a student's situation and provide the appropriate instructions in the same way a human tutor would.
4. **Communication knowledge:** this component takes charge of the communications between learners and the system - including the user interface, human-computer dialogue and pictorial agents.

Self-regulated learning

A learner should be considered as an active learner rather than a passive one by educators. Many researchers have already indicated that it is very important learners, rather than their instructors, take the main responsibility for their study. A competent learner should be fully aware of his/her abilities and initial knowledge level and set up learning goals based on self-evaluation. Then the learner applies appropriate strategies, and keeps adjusting these, in order to achieve the set goals (Zimmerman, 1990).

These are so-called 'self-regulated learners' or as Pintrich (2000) defined: self-regulated learning is an active and constructive process where a learner controls his/her cognition, motivation and behaviour to achieve their set learning goals. In so doing this, learners better meet the demands of a lifelong learning society and one of the main higher education goals - to foster undergraduate students as self-regulated learners. Self-regulated learning abilities have strong positive impacts on students' learning outcomes, so for teachers and instructional designers, it is very important to guide and support students to learn actively and take responsibility for completing learning tasks. Just-in-time prompts, adaptive feedback and scaffolding which can help students self-assess or seek help, are the effective teaching strategies commonly put into use.

Research methods

This study applied meta-analysis as the main research method. As Glass (1976) defined, meta-analyses integrate and analyze different research on a specific topic by using content analysis and statistical methods. Compared with traditional literature review methods, the main advantage of meta-analysis is that it can provide summary quantitative results by using statistical methods to analyze each individual study and identify different sample sizes and judge research quality.

This study aims to survey the empirical research on ITS which can foster learners' self-regulated learning abilities. So, for the purpose of this study, we selected empirical research which focused on designing, implementing or evaluating an ITS to foster student's SRL skills. Because of the topic's inter-disciplinary nature, we started our search from two main sources - engineering (Compendex, Sciencedirect, Scopus, and Springer Link) and education (Education Research Complete, ERIC, NZCER Journal Online and ProQuest) databases.

A total of 113 articles (dating from 1998 to 2014) were found using a combination of keywords: self-regulated learning/learner and intelligent tutoring system/intelligent tutor. The 113 articles included 76 journal articles, 15 conference articles, 11 monographs, 6 dissertations, 2 book chapters, 2 generic articles and 1 report. After reviewing all of these, 53 articles were then selected as meeting our selection criteria. The authors designed a full-scale coding protocol based on the research questions. It helped us collect and analyze the information from all the studies.

Research questions

What models of self-regulated learning have been used to guide system design?

Several models of self-regulated learning have been used to guide system design:

Zimmerman's SRL model (2001) described the whole SRL process in three steps: planning, practicing and evaluating. For planning, a learner assesses previous knowledge, analyzes learning tasks and makes a plan. Then, for practicing, they will apply appropriate learning strategies to achieve the sub-goals according to the learning plan. Finally, they will evaluate the learning outcomes to decide whether to maintain original their tactics or adopt new ones.

Winne and Hadwin's SRL model (1998) is also commonly applied in this field. This model contains four sub-processes (D. Moos, 2013):

1. Task analysis: when students accept assignments, they will analyze the learning tasks, evaluate the learning environment and available resources, and estimate the domain knowledge level and learning skills.
2. Goal setting and plan making: after task analysis, the student will have a good understanding of the situation, and will then set up reasonable learning goals and make plans accordingly.
3. Strategy implementation and monitoring: when the learning process starts the student applies his/her skills or familiar learning tactics. The learner then keeps monitoring their progress and adjusts the learning strategies to adapt to new situations.
4. Reflection for future study: after completing the learning tasks, students will learn from the experience, and make any necessary changes for future learning.

Pintrich's model (2000) emphasized the relationship between learner's self-regulation actions and the learning environment and specifically described the cognitive, motivational, behavioral and contextual factors involved in the SRL process. There are also four phases in this model (Schunk, 2005). The first phase is forethought, planning, and activation, which is followed by the monitoring phase. The third phase is the control stage, with the last phase being reaction and reflection.

These classic models were the ones most commonly applied in designing an ITS which can foster student's SRL abilities but they were not specific enough to fully guide ITS development. So some researchers also set up their own SRL models:

Azevedo's SRL model was developed based on Winne and Hadwin's, and Pintrich's SRL model. This model has 33 self-regulatory variables to describe accurately the meta-cognitive procedures. These variables are distributed in several learning activities: planning activities; monitoring activities; learning strategies implementation; task difficulties handling and demands; interest statement.

In addition, (Aleven, Mclaren, Roll, & Koedinger, 2006) designed the ITS help tutor based on **Nelson-LeGall's help-seeking model** (1981). This model resolved the whole help-seeking process into five sub-steps: after self-assessment and task analysis, the learner realizes that they need help. The learner evaluates the advantages and disadvantages of seeking help and starts to look for potential support. After investigation and comparison, the learner implements help-seeking strategies to ask for help and reviews and evaluates the help-seeking process.

What options are available to measure learners' self-regulated learning skills?

Intelligent tutoring systems can produce **learning analytics**, by collecting dynamic data about every interaction between learners and the system. This includes the notes students take using the system tools, the time students stay on a specific page, the students' movement from one topic to another and the hints students request. All this data can be considered as a set of event data which happens throughout the journey of self-regulated learning (Aleven et al., 2010), which may be considered more accurate and unobtrusive than the student's self-reported data and also more abundant and diverse than static data. This data will also help the ITS improve its reasoning abilities and help provide context-sensitive prompts and hints to learners.

Some of the studies chose quasi-experimental research as the final evaluation – short-term experiments lasting from 2 hours to 2 days, to longer evaluations lasting for a semester. Others evaluated the ITS's effectiveness by comparing a group's pre- and –post test results. The samples chosen were from primary school, middle school to university students and were small-sized - from 4 students to 219 students. The data collected for measurement was diverse:

1. Online tracking data: such as student log files, eye-tracking data, facial recognition, and human-agent dialogue.
2. Self-reported data: including think-aloud protocol, student self-assessment and help-seeking behavior.
3. Paper-and-pencil questionnaires on students' self-regulated learning skills.
4. Pre – post tests of domain knowledge to compare the variation of learning outcomes caused by ITS with different intervention means.

What scaffolding approaches are used to foster learners' self-regulated learning skills?

We found some distinct scaffolding in these studies to foster students' SRL abilities. Some scaffolding approaches were focused on specific phases, such as help-seeking and self-evaluation, while others used the entire action flow of SRL. The main modes of presentation were just-in-time prompts and adaptive feedback. The timing of a prompt's appearance (just-in-time or delayed) and the content of the feedback (context-sensitive or context-insensitive) were the primary definitive factors in SRL development. The specific scaffolding methods used are discussed in the following sections.

Help-seeking and self-assessment

Help-seeking, as an effective self-regulated learning strategy, was extensively studied in the classroom instruction environment but less explored in interactive learning environments. Research results revealed that students lacked help-seeking abilities and consequently either overused help facilities to get the answers directly or ignored the help facilities (Aleven et al., 2006). Aleven et al developed a help tutor to work together with an existing ITS (the Geometry Cognitive Tutor) in order to improve students' help-seeking skills by providing adaptive feedback and on-demand support. The geometry cognitive tutor was designed for a high school geometry curriculum. Students mastered knowledge by solving real-world problems and got just-in-time feedback from the system.

There were two main kinds of on-demand support: context-sensitive hints and a context-insensitive glossary. The context-sensitive hints were tailored to the learner's situation but the context-insensitive glossary was used to encourage learners to look for the information they needed by themselves. The system applied a Bayesian network to evaluate students' learning progress: if a student was new to the topic, the system would give him/her context-sensitive hints; if the system evaluated that the student was familiar with the topic, he /she would be encouraged to first use the context-insensitive glossary. The help tutor could evaluate automatically, and undetected, whether students' help-seeking behaviors were appropriate or not and, according to the evaluation results, the tutor then provided adaptive feedback which could improve learners' help seeking abilities.

Other researchers working with the same Geometry Cognitive Tutor, extended the help tutor to a help-seeking support environment: this included an updated help tutor and a self-assessment tutor (Roll, Aleven, McLaren, & Koedinger, 2007). The updated help tutor offered students more instructions to enable them to realize the principles and benefits of help-seeking, instead of merely providing the answers to questions or the direction of the next learning step.

Because of the close relationship between self-assessment and help-seeking, this help-seeking support environment involved the self-assessment tutor. When a learner worked through a problem with the system, it would offer self-assessment scaffolding through four sub-steps:

1. Prediction: a learner predicted their own ability to solve a problem correctly. At the start, before the learner solves a problem, the system would ask the student whether they were able to solve the problem without any help. If the learner answered 'yes', then they would move on to the second step; if the answer was 'no', the hints would appear (Roll, Aleven, McLaren, & Koedinger, 2011).
2. Motivation: the system asked the learner whether they would try to solve a problem or not.
3. Reflection: after giving the answer to the question, the learner could figure out whether their prediction was right or not. This step was very important for the learner's self-reflection and it would help the learner improve the accuracy of their self-assessment (Roll et al., 2011).
4. Projection: based on all the results, the learners would estimate their actual self-assessment skills. It would improve their SRL skills in future.

In addition, the researchers gave students a short classroom instruction prior to the students beginning to learn with the system. The aim of the classroom instruction was to help students establish correct attitudes towards help-seeking.

In another study (Long & Aleven, 2013), the self-assessment tutor was redesigned with three additional features to the geometry cognitive tutor's open learner model. In accordance with the educational experiment's results, the researchers chose these new features to add self-assessment prompts, showing student's knowledge progress information by problem difficulty level and these delayed the appearance of a knowledge progress bar. The purpose of this delaying of the appearance of the knowledge bar was not only to help students focus on their study but also to give them sufficient time for self-reflection.

Prompt and feedback

As a computer-aided instructional system, an ITS always places a student alone to work on a particular learning task at their pace. Therefore, student attention is easily diverted, increasing the chance of the student getting lost and frustrated. Here feedback, as a crucial part of computer-aided instruction, is more directed at learning tasks which result in helping students succeed in acquiring new knowledge and achieving their academic goals. Feedback also has positive impacts on students' self-efficacy and self-esteem. Studies in this field adopted educational experiments (Azevedo, Cromley, & Seibert, 2004; Azevedo, Cromley, Winters, Moos, & Greene, 2005; Bouchet, Harley, Trevors, & Azevedo, 2013) to compare the learning outcomes caused by different combinations of prompts and feedback. Researchers explored different settings, such as, prompts only; prompts with feedback; fixed prompts or feedback; adaptive prompts and feedback according to the student model.

Study choice

Another research project redesigned the geometry cognitive tutor in order to enhance learners' study initiatives (Long & Aleven, 2013) and here the system did not provide exercise questions in a sequential order. In this instance every question had its own difficulty level and each difficulty level had a few different questions. The aim of the questions was to make sure that when a student completed all the questions at a certain level, they really did achieve this knowledge level and that, moreover, students understood what knowledge they had already mastered and what they had not. When a student completed a question, they could choose what level to continue on. The researchers also added game features to increase the fun and compensate for when students faced complex and unfamiliar science topics.

Concept-mapping

Betty's Brain, a teachable ITS which helps students learn ecosystems, used concept mapping as a form of scaffolding. Concept mapping is a method of visualizing information - which is conducive to a more comprehensive and deeper understanding of key knowledge points and their relationships (Biswas, Roscoe, Jeong, & Sulcer, 2009; Biswas et al., 2004).

Learning by teaching

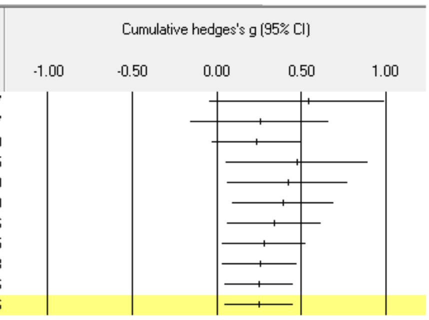
Another way to foster student's SRL skills is learning by teaching. Researchers (Biswas et al., 2009; Biswas et al., 2004) believed that, in essence, the SRL process was as analogous to the teaching process: they both needed to analyze tasks, make plans, monitor the teaching/learning process and the context, retain consistent strategies or adjust to new ones and self-reflect for future proposed study. So the ITS they designed, Betty's Brain, was taught ecosystem knowledge by students. Students became the tutors, and they assessed their academic performance by examining the system's knowledge progress.

How effective are intelligent tutoring systems in improving students learning outcomes?

We used Comprehensive Meta Analysis (CMA) software to calculate the effect size of ITS impacts on student academic performance. Because of the small sample size for most studies, we chose Hedge's *g* as the effect size index of this research. The Hedges' g was the differences of treated group and control group in an individual study. From all 53 articles, we chose ten independent studies (which reported 25 dependent variables of treated group's and control group's learning outcomes). These ten studies were chosen because they compared learning outcomes caused by traditional classroom instruction with those resulting from an ITS which included an SRL mechanism. Moreover, the samples from different research were diverse, from primary school students to university students, and the sample size ranged from 4 to 219. Based on the wide range of that sample size, we chose the random model's results (in preference to using a fixed model).

Table 1: Cumulative statistics of ITSs' effective size

Model	Study name	Outcome	Cumulative statistics						
			Point	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
	Azevedo	Learning	0.541	0.295	0.087	-0.038	1.120	1.832	0.067
	Azevedo	Combined	0.258	0.208	0.043	-0.151	0.666	1.236	0.217
	Azevedo	Combined	0.240	0.137	0.019	-0.028	0.509	1.752	0.080
	Azevedo	Combined	0.479	0.214	0.046	0.059	0.899	2.236	0.025
	Bouchet	Combined	0.422	0.182	0.033	0.065	0.779	2.320	0.020
	Moos 2011	Score	0.397	0.154	0.024	0.095	0.698	2.578	0.010
	Biswas	Combined	0.343	0.142	0.020	0.064	0.622	2.406	0.016
	Chen 2009	Score	0.283	0.127	0.016	0.035	0.531	2.238	0.025
	Ifenthaler	Combined	0.257	0.113	0.013	0.036	0.479	2.279	0.023
	Kauffman	Combined	0.252	0.104	0.011	0.047	0.456	2.412	0.016
Random			0.252	0.104	0.011	0.047	0.456	2.412	0.016



Results showed that no ITS in this field had a negative impact on students' learning outcomes. The overall mean effect of the various ITS interventions, *g* =0.252, showed that these types of ITS have small positive impacts on learners' academic performance (95% confidence interval [0.047, 0.456], $p < 0.05$). p=0.016, which was significantly different from zero.

What are the features of such intelligent tutoring systems?

The ITS were developed by two different approaches: one was to design an ITS which included the SRL mechanism, while the other was to add the SRL mechanism to an existing ITS.

Extend SRL modules with an existing ITS system

The Geometry Cognitive Tutor (Aleven et al., 2006) was designed using a model tracing algorithm, which meant that students needed to follow the right solutions when they solved problems: if they did not, they would be corrected by just-in-time prompts and adaptive feedback. On the basis of this ITS, researchers kept designing add-on agents to improve learner's SRL skills, such as the help tutor (Aleven et al., 2006) which improves learners' help-seeking skills, the self-assessment tutor (Roll et al., 2011) which helps students evaluate their learning progress and the study initiative tutor (Long & Aleven, 2013) to give the learning control rights to students rather than the system.

Design an ITS for SRL

Meta tutor, (Azevedo et al., 2004; Bouchet et al., 2013; Greene, Costa, Robertson, Pan, & Deekens, 2010; D. C. Moos, 2014) is a human circulatory system tutor which contains 4 pedagogical agents to foster student's SRL skills. It presents 41 pages of learning content with text or diagrams in a non-sequential order. Students can use the table of contents to choose different sub-topics. The four pedagogical agents (Gavin, Pam, Mary and Sam) provide adaptive prompts and feedback to students for SRL purposes: Gavin is the information guide for student navigation; Pam takes charge of setting up learning goals and making plans; Mary monitors student actions to guarantee that they will attain the goals; and the final agent, Sam, provides diverse learning support tools so that students can adopt the learning strategies they want. These teaching agents, therefore, take care of the student's whole SRL process.

The other fully-developed ITS in this field is Betty's Brain, an intelligent teachable tutor which can teach students ecosystems knowledge and also foster their SRL skills. The main feature of Betty's Brain is that in this system, students are the instructors who will teach the system to learn domain knowledge. The developers' philosophy was that student's SRL is consistent with a teacher's teaching process. Thus, letting students execute the teaching tasks will help them become active learners with high level SRL skills.

The two main features of these types of ITS were:

Model-tracing ITS. Most of the ITS in this field were model-tracing intelligent tutors. Model-tracing tutors contain a cognitive model of the domain, which helps the system check students' responses and make sure they are on the right track. If students have gone off track, the system guides them by providing prompts or feedback.

Model-tracing tutors lead to effective ITS but take a long time to develop - especially for building the cognitive model. Therefore some researchers have developed specialized authoring tools for model-tracing tutors in order to save time and reduce difficulties. An example is the Geometry Cognitive Tutor which was developed using a model-tracing tutor authoring tool.

Multi-agent system. Some of these types of ITS were multi-agent ITS. A multi-agent system was adopted to solve complex problems which cannot be done by an individual intelligent agent. In these systems, the designers applied different agents to guide or support every stage of a student's SRL process. For example, the Meta tutor (Bouchet, Harley, Trevors, & Azevedo, 2013), applied the four pedagogical agents (Gavin, Pam, Mary and Sam) to provide adaptive prompts and feedback to students for SRL purposes.

Conclusion

The results of this research support the idea that an ITS is an effective teaching method to foster student's SRL abilities. Preliminary meta-analysis results imply such ITS have a small positive impact on student's learning outcomes. In this field, most of the ITS were designed for STEM (Science Technology Engineering and Mathematics) subjects. ITS can help students learn such complex topics without creating huge cognitive overload. Compared with classroom instruction, these kinds of intelligent tutoring systems use learning analytics and collect event data to measure a learner's SRL progress, rather than using self-reported data. This method of collecting data can also aid the system's decision making and evaluation. The main modes of scaffolding were prompts and feedback. The timing of a prompt's appearance (just-in-time or delayed), and the content of the feedback (context-sensitive or context-insensitive) had a significant influence on a student's learning outcomes. The SRL mechanism could be embedded in an ITS from the point of initial design or be retro-fitted to an existing ITS as add-on agents afterwards. Most of the systems were model-tracing ITS and multi-agent systems.

This study only compared the learning outcomes caused by traditional classroom instruction and an ITS which included an SRL mechanism. We did not explore the differences of academic performance caused by standard ITS and an ITS with an SRL mechanism. Moreover, this study did not analyze the variance of SRL abilities caused by using an ITS with an SRL mechanism. These will be the subject of future research.

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