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Intelligent Tutoring Systems in Higher Education – Towards Enhanced Dimensions

Abstract

This paper describes how intelligent tutoring systems (ITSs) improve flexible learning in higher education. The benefits of ITSs over course management systems (CMSs) are discussed, and we demonstrate how the traditionally used dimensions of flexibility can be enhanced to tackle the challenges that higher education is facing from an abundance of online educational products and services. In addition, a new data-driven approach to analyzing questions about flexible learning is suggested, which could lead to better-optimized settings for flexible learning.

Keywords

flexible learning, intelligent tutoring systems, computer-assisted learning, education, artificial intelligence

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1 Introduction

Flexible learning is one of many research topics in the field of education that has recently attracted much attention (LI & WONG, 2018; TUCKER & MORRIS, 2011; IRVINE & COSSHAM, 2011; CASEY & WILSON, 2005; LING et al., 2001; COLLIS & MOONEN, 2002). Much of this interest stems from the availability of a plethora of learning and teaching options and strategies using digital technologies and opportunities to address current learning challenges (LI & WONG, 2018; BATES, 2001; VAN DE BRANDE, 1993). New forms of learning enabled by such technologies, such as access to learning materials at any time and in any location, or even studying over distance would be intuitively termed "flexible." The impact of technology on education and flexible learning, in particular, has been so strong that many use the term flexible learning synonymously with "open learning," "distance learning," or "technology-mediated learning" (IRVINE & COSSHAM, 2011). Often, flexible learning is discussed in the context of technology — in particular for CMSs, whose components, properties, and functions are related to crucial aspects of flexible learning (DE BOER & COLLIS, 2005). Similarly, this paper analyzes the benefits of using ITSs in the context of flexible learning while being guided by the following questions: What aspects (or dimensions) are most crucial for flexible learning? What dimensions enhance learning and under what circumstances? How can flexible learning be implemented efficiently?

2 Flexible Learning

Recent research into flexible learning has focused on a few key aspects. Besides implementations, one goal is to extend the notion of intuitively agreeable forms of flexible learning to encompass all possible aspects or "dimensions," as some authors describe them (e.g., LING et al., 2001 or COLLIS & MOONEN, 2002), and to give them a general definition. This current lack of a general definition is considered counterproductive by COLLIS & MOONEN (2002), although it may have helped the field of flexible learning to gain momentum and develop in many relevant directions. LI & WONG (2018), DE BOER & COLLIS (2005), and COLLIS & MOONEN (2002), have contributed towards formalizing the notion of flexible learning (see LI & WONG (2018) or TUCKER & MORRIS (2011) for a more recent analysis of the existing literature and ongoing discussion about the definition of flexible learning). This recent trend involves establishing a formal definition by describing the notion of flexible learning either using distinctions from other well-known learning concepts such as "open learning," "distance learning," and "technology-mediated learning," or by describing all the relevant dimensions that play a role in learning, such as time and content.

COLLIS, VINGERHOETS, & MOONEN (1997) provides a complete list of the dimensions used to study flexible learning through a literature review and surveys. In COLLIS & MOONEN (2002), technology, pedagogy, implementation, and institution are identified as core components for study when developing an understanding of flexible learning, with "learner choice" at the center. A more balanced approach would be to analyze who should have what choices, determined by theoretical considerations and empirical evidence upon using data analysis. The use of ITSs and methodologies from educational data science are critical tools in this development. A recent review by LI & WONG (2018) lists relevant dimensions and scientific studies, together with corresponding findings. These dimensions are time, content, entry requirement, delivery, instructional approach, assessment, resource and support, and orientation or goal. There are several examples of implementations of flexible learning at universities, which have shown considerable success, including MÜLLER, STAHL, ALDER, & MÜLLER (2018) and DE BOER & COLLIS (2005).

3 Intelligent Tutoring Systems (ITSs)

Personalized learning, with tutors actively mentoring students, is one way to ensure learning is adapted to student needs, and it has been highly effective (HATTIE, 2008). There have also been attempts to emulate human tutors using computers such as with ITSs (MA, ADESOPE, NESBIT, & LIU, 2014; ANDERSON, BOYLE, & REISER, 1985), designed to make personalized learning accessible to everyone. ITSs are computer system designed to instruct students to study topics according to their needs by the automatic generation of individualized content, grading, feedback, instructions, or progress tracking. Formally, ITSs have the following structure (NKAMBOU, MIZOGUCHI, & BOURDEAU, 2010; NWANA, 1990):

A domain model (cognitive or expert knowledge model built on a theory of learning)
A student model (cognitive and affective states and their evolution as the learning process advances)
A tutoring model (gets input from above layers and implements tutoring actions)
A user-interface model

Figure 1: Structure of ITSs

Below is a description of several key components of ITSs related to the above structure that are beneficial for our discussion on flexible learning and highlight the advantages of ITSs over CMSs.

Progress Tracking

Firstly, ITSs use advanced models to track students' progress and assess their cognitive state. A component of this is knowledge tracing (KT) — a class of models designed to trace states of knowledge using interaction data (inputs during problem-solving exercises). The most prominent type is Bayesian knowledge tracing (BKT) (CORBETT & ANDERSON, 1994) and its variants. A more recent KT approach uses recurrent neural networks (RNN) and is called deep knowledge tracing (DKT) (PIECH et al., 2015). Most KT models rely on exercise tags and the results – whether the exercises were solved correctly or not – to learn to predict the outcome of future interactions. The clustering of students is another means of analyzing groups of students and estimating their cognitive state.

There have also been attempts to estimate the affective state of students using new models and data from wearable technology (SANO, 2016; WATANABE, MATSUDA, & YANO, 2013). Moreover, cognitive neuroscience attempts to understand aspects of learning that help to select the right cognitive model for ITS systems (GABRIELI, 2016; SARRAFZADEH, ALEXANDER, DADGOSTAR, FAN, & BIGDELI, 2008; REDCAY et al., 2010). ITSs also enable the collection of rich interaction data.

Content Generation

The second main advantage of advanced ITSs is that they can generate content automatically. We will consider examples of automatically generated content from my own ITS implementation, which deals with the application of ITSs in mathematics education. In the context of ITSs, several forms of content (exercises, theory sheets, etc.) can be generated automatically while taking account of different parameters, including the difficulty of exercises, the form of crucial aspects of exercises (such as the form of the parameter in an equation), the skills needed to solve exercises, and many other factors.

Instructional Aspects

In terms of instructional approaches, advanced ITSs allow for considerable flexibility (MA, ADESOPE, NESBIT, & LIU, 2014; POLSON & RICHARDSON, 2013; ANDERSON, BOYLE, & REISER, 1985). When it comes to enabling students to acquire skills and teaching them problem-solving techniques, educational institutions, instructors, and students can all benefit. This aspect, coupled with content generation above, indicates huge pedagogical potential, allowing for individual learning paths while providing institutions with a clear picture of the courses they offer. The instructor can monitor students in real-time and offer assistance as necessary while students benefit from access to an array of individualized learning materials.

4 Enhancing Flexible Learning Through ITSs

4.1 ITSs as an Extension of CMSs

From the outset, it is evident that ITSs far exceed CMSs in terms of functionality. In this paper, I am assuming ITSs, when implemented, include all the functions offered by CMSs, although ITSs suitable for application in learning institutions must satisfy this condition. Indeed, such systems have already been successful for many years in universities and schools (MA, ADESOPE, NESBIT, & LIU, 2014; KOEDINGER, ANDERSON, HADLEY, & MARK, 1997).

Most universities nowadays use some form of CMS to provide students with a degree of flexible learning. However, the question remains as to whether, in an era of artificial intelligence, the flexibility offered by CMSs accurately reflects the needs of students and provides solutions to the challenges currently faced by universities. This paper argues that although CMS-based progress in flexible learning is both positive necessary, greater benefit would lie in more advanced options in flexible learning related to content, assessment, and instructional approaches. Analogous to the CMS discussion in DE BOER & COLLIS (2005), the components of ITSs and their corresponding functionalities can be analyzed and related to the studied dimensions of flexible learning. The following section will focus on the dimensions from which the highest ITS gains might be expected in terms of flexibility. Figure 2 depicts the additional possibilities of commonly used dimensions.

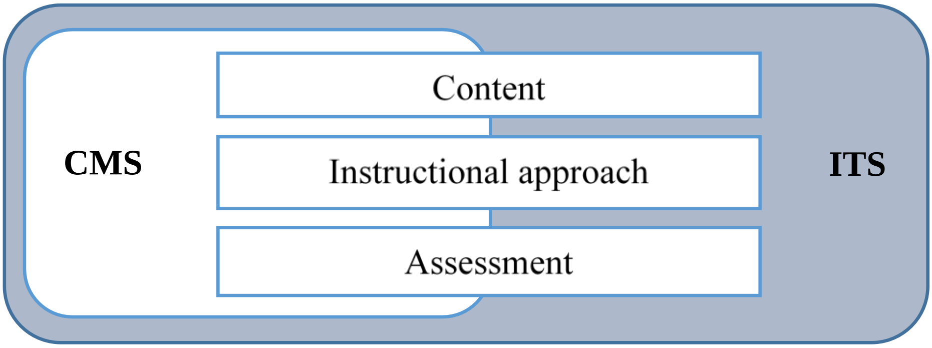

Figure 2: Relationship between CMSs and ITSs and extended dimensions content, instructional approach, and assessment

4.2 Content-, Assessment-, and Pedagogical Flexibility Through ITSs

Although flexible learning can exist without the application of technology, some features are not feasible unless advanced technologies such as ITSs are used. These aspects are crucial for pedagogical considerations and the efficacy of learning when considering any scenario other than for one-to-one tutoring. The terms "pedagogy" and "instructional approaches" are often used synonymously in the literature (e.g., COLLIS & MOONEN, 2002). The following sections discuss content, instructional approaches, and assessment in detail and outline how they are refined by ITSs.

Content

In the context of CMSs, the flexibility of content is discussed in all the relevant literature including LI & WONG (2018), DE BOER & COLLIS (2005), and COLLIS & MOONEN (2002). In the realm of ITSs, however, this aspect can be far more powerful. As already discussed, automatic generation of content is one of the essential features of advanced ITSs, and one particular case is highlighted here.

A student learning to solve linear equations may have problems tacking such a task for many different reasons. For a start, the type of linear equation might be too difficult, which can have a variety of causes. With access to ITSs, the student can let the computer program generate linear equations with specific properties and levels of difficulty (see Figure 3); automatic explanations, hints, and step-by-step solutions can be generated. Tasks can also be transformed from algebra exercises (for which the student must apply the usual rules until he or she arrives at a solution) to multiple-choice exercises at any stage in the problem-solving process (see Figure 5). Figure 4 shows an example of how ITSs help generate content fully automatically when entering the number of distinct complexity classes (i.e., number of different levels of difficulty) and the kind of parameters (e.g., integer coefficients or integers and rational numbers, etc.). The examples cited here are from my own implementation of ITSs.

Instructional Approaches

Flexibility in instructional approaches is considered more challenging to implement because of the additional workload for instructors and gaps between what students want and what instructors can provide (TUCKER & MORRIS, 2011). ITSs can help here by providing essential incentives as well as additional insights for instructors. Some authors conclude from their studies that flexibility is only desired by students in a small number of specific aspects (TUCKER & MORRIS, 2011). We would expect a very different outcome for the same dimensions in other settings. For instance, the application of ITSs in mathematics education offers new options to students, which are highly likely to be used and appreciated since they contain some of the features of human tutoring that have proved so efficient (HATTIE, 2008). Figure 4 depicts a learning mode in which the student can solve exercises step-by-step while receiving instructions in various forms, as well as immediate feedback. Figure 5 shows how, when encountering difficulty, a student can ask for a multiple-choice choice form of the same question.

Automatic and Dynamic Assessment

Another critical benefit of ITSs is the possibility of automatic grading and other forms of assessment. This gives the student the option of receiving ongoing feedback by self-testing with automatically generated tests and solving problems in an exercise-solving mode. Furthermore, the instructor can choose from a range of assessment options, allowing for a variety of subject-specific tests that vary in content and form. Obviously, this is only feasible in systems such as ITSs, which assist the instructor. Moreover, such systems give teachers the flexibility to decide on the amount of information and instruction provided to students.

Class of Complexity	Complexity	Problem	Solution	Hints
0	0.06	$7 \cdot x = 9 \cdot x$	$x = 0$	Simplification Left; Divide both sides by constant;
0	0.11	$-7 \cdot x = 8 \cdot (x - x)$	$x = 0$	Remove parenthesis; Use the associativity law; Divide both sides by constant;
0	0.13	$4 \cdot x = -7 - 7$	$x = -\frac{7}{2}$	Divide both sides by constant;
0	0.18	$x = 2 \cdot (-7 \cdot x + 2 \cdot x)$	$x = 0$	Adding elements + multiplication ; Divide both sides by constant;
1	0.25	$5 \cdot (8 + (7 + 5)) \cdot x = -x$	$x = 0$	Adding elements; Adding elements + multiplication ; Divide both sides by constant;
1	0.28	$-7 \cdot x = -7 \cdot (h - 6) \cdot x$	$x = 0$	Use the distributivity law; From l.h.s. to r.h.s.; Divide both sides by constant;
1	0.33	$4 \cdot (-3 + (-9 + 5) \cdot x) = 4$	$x = -1$	Adding elements + multiplication ; From l.h.s. to r.h.s.; Divide both sides by constant;
1	0.33	$5 = 6 \cdot (\frac{6}{8} + (6 - 1)) \cdot x$	$x = \frac{10}{69}$	Adding elements; Adding elements + multiplication ; Divide both sides by constant;

Figure 3: Example of content generation with specific levels of difficulty and simple hints.

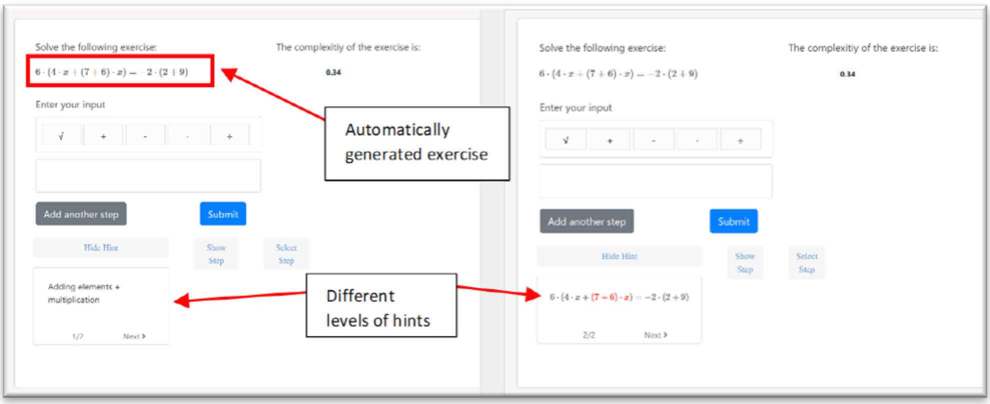

Figure 4: Showing hints of different types for given exercises. On the left, we see the presentation of a hint in words. By clicking on "Next," the same hint is highlighted in the equation.

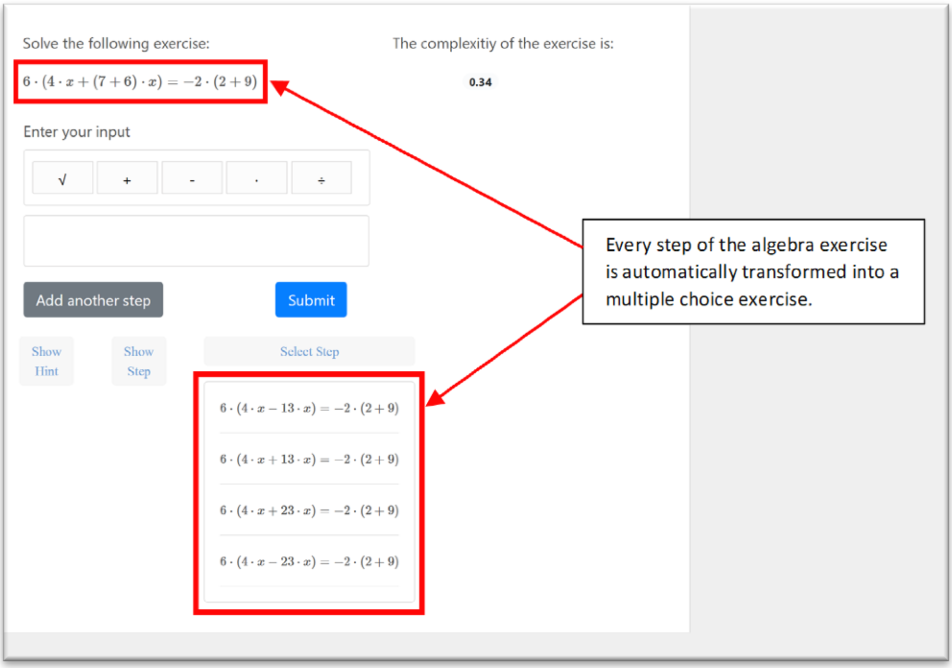

Figure 5: Transforming an exercise from an algebraic to a multiple-choice format

5 Traditional Higher Education and ITSs

There are many ways to utilize ITSs in higher education. The meta-analysis (MA, ADESOPE, NESBIT, & LIU, 2014) suggests that using ITSs could be as efficient as learning individually with a human tutor. It also stresses that ITSs should not be considered a replacement for other modes of instruction, but rather a complementary tool. In this section, I will briefly describe two scenarios likely to enhance learning and demonstrate the benefits of this flexibility with respect to the dimensions discussed above.

In the figure below, “L” stands for lecture and “E” for exercise class or lab. Dashed arrows indicate human input.

Figure 6 depicts the scenario in which an ITS is used only in exercise classes. The instructor of the lecture and the exercise class tutor can influence the ITS’ working in many different ways, including determining the range of difficulty, topics covered, flexibility with respect to content, etc. In this model, the class has aspects of conventional exercises classes as well as interactions with the ITS. The students interacting with the ITS have all the features outlined in Section 4.

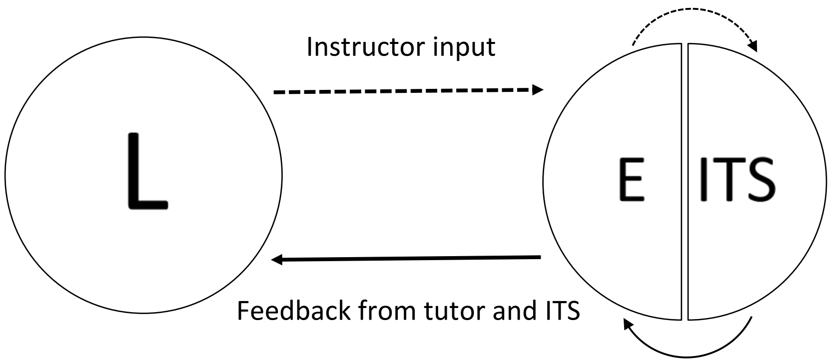

Figure 6: Traditional lecture and ITS-supported exercise class

Figure 7 shows a scenario in which an ITS is used in both lectures and exercise classes. The student interaction data in both settings are used to provide instructors and tutors with information related to the learning state of the students. The instructor can use the ITS in the lecture to ask the students to answer theoretical questions, solve quizzes or simple exercises, or work through a mathematical proof.

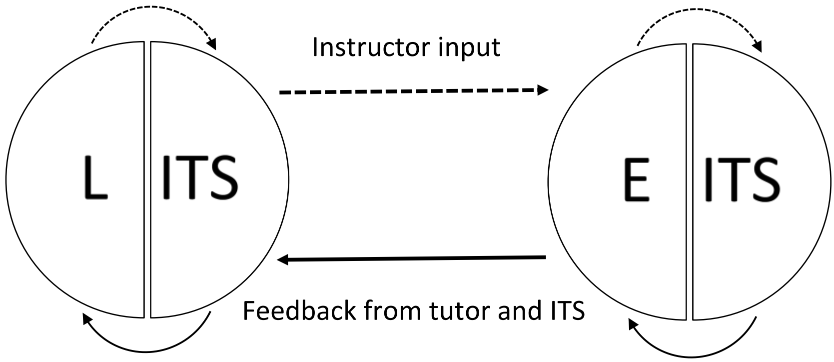

Figure 7: An ITS is used as part of the lecture and in the exercise class to support both students, instructors, and tutors

All data collected during the interaction between students, instructors, and tutors and ITSs are valuable for analyzing the effectiveness of flexible learning and will feed into future research.

6 Conclusion

Higher education institutions face competition from many online learning products and services, such as open online courses and other forms of learning in the private sector. ITSs, which enable personalized learning, dynamic assessment, and individual learning paths, could help overcome these challenges in combination with the traditional strengths of universities. However, ITSs are costly and rely on both technical and pedagogical specialists to implement models such as the two outlined above, while ensuring the system delivers all the requirements set by instructors and institutions. The new possibilities offered by ITSs raise many questions and require careful planning as well as constant analysis of the effect that these new teaching methods have on students.

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