Proposal for Developing an Autonomous Intelligent and Adaptive E-Learning System (AIAES) for Education

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***Abstract**. Intelligent tutoring systems are among the most recent advances in educational technology, being recognized as powerful adaptive educational systems providing services and modules for personalized learning to students with varying backgrounds, abilities, behaviours and knowledge. Proposals are presented for construction of an Autonomous Intelligent and Adaptive E-learning System (AIAES) for education based on assignments, tasks and exercises for the improvement of information literacy.*

Keywords. e-learning systems, intelligent systems, adaptive learning systems

1 Introduction

Intelligent tutoring systems (ITS) are among the most recent advances in educational technology (Sani & Aris, 2014). ITSs are powerful adaptive educational systems, providing services and modules for personalized learning to students with varying backgrounds, abilities, behaviours and knowledge (Crockett, Latham, & Whitton, 2017).

ITSs are software systems designed to use artificial intelligence technologies to provide individualized/personalized instruction to students based on their profiles (Aparicio, De Buenaga, Rubio, & Hernando, 2012; Crockett et al., 2017; Lo, Chan, & Yeh, 2012). The goal of any ITS system is to provide an immediate and efficient solution to a student's learning problems and to help the student achieve maximum learning gain. To achieve this, ITS builds a model of the goals, preferences and knowledge of each student, and uses this model to provide a degree of intelligent assistance (Crockett et al., 2017). Each individual student is provided with the learning content and instructional methodology that best suits his or her personal needs.

The architecture of an ITS is always designed with the following principles: whom to teach (student module), what to teach (domain module), how to teach (pedagogical/instructor module) and the user-system interaction environment (interface module) (Sani & Aris, 2014). The student module is the basis for making the ITS adaptive and is responsible for managing the cognitive state by creating a student's profile that includes information such as the student personal data, preferences, current level of knowledge, etc. The instructor module is responsible for making instructional decisions related to the pedagogical aspects of learning, such as (1) correct choice of teaching methods and learning materials that best suit an individual student's profile; (2) deciding on the appropriate time to present the content; (3) assessing the cognitive state of the individual learner, and (4) deciding whether the student is able to proceed to the next learning stage.

There is a range of techniques that can be used for modelling students and instructors. In the existing literature, ITS solutions were designed and proposed based on techniques such as ontology (Grubišić, Stankov, & Peraić, 2013; Kumar, Gress, Hadwin, & Winne, 2010), neural networks (Cabada, Barrón Estrada, & Reyes García, 2011), data mining (Lin, Yeh, Hung, & Chang, 2013; Roll, Aleven, McLaren, & Koedinger, 2011), collaborative filtering (Roll et al., 2011), fuzzy logic (Dias & Diniz, 2013; Voskoglou, 2013), intelligent agents (Mikic Fonte, Burguillo, & Nistal, 2012; Yaghmaie & Bahreininejad, 2011), and Bayesian Network (Conati, 2010; Grubišić et al., 2013). Among these, Bayesian techniques and fuzzy logic have been found to be the most promising in handling uncertainty issues in modeling students and instructors (Sani & Aris, 2014).

An Autonomous Intelligent and Adaptive E-learning System (AIAES) supporting the cognitive learning approach (Dolenc & Aberšek, 2015) is planned to be developed. The work on design, testing and validation of AIAES with assignments, tasks and exercises for the improvement of information literacy (Šorgo, Bartol, Dolničar, & Boh Podgornik, 2017) among adolescents and their educators is in progress.

The project has received a three-year grant and is assigned to Universities of Maribor and Ljubljana, along with the private college of DOBA, in Maribor. The work in progress started in May 2017 and is planned to be finished in April 2021.

2 Perspectives on the application of Autonomous Intelligent and Adaptive E-learning Systems in education

Much has been said about the potential of new technologies to transform education and training, but only a handful of these statements have been supported by research or even tested by thorough scientific research. Following the initial testing of programmed instruction, Skinner believed that Learning Machines could be an excellent means to save teachers' time and facilitate their work. If a teacher relegates to the machine those learning tasks that can be mechanized, then he is free to perform the irreplaceable human tasks in the learning process (Skinner, as cited in Dolenc & Aberšek, 2015).

Learning with technology refers mostly to situations when technology is used with the purpose of encouraging learning. Today's term “learning with technology” mostly reflects what Lowyck (Lowyck, as cited in Dolenc & Aberšek, 2015) calls “a common impulse to (try to) use available technology for schooling purposes”. The explosion of personal computers with the potential for internet connection in the second half of the 20th century revolutionized the way we communicate and has therefore profoundly influenced learning and teaching. At this stage we need to distinguish between two different directions: technology-oriented and learning-oriented approaches to teaching (Dumont, Istance, & Benavides, 2010). In the technology-oriented approach, the use of technology is at the center of education, enabling access to the latest technology.

What is therefore wrong with the technology-oriented approach? The major problem with this approach is that in the 20th century it underwent numerous important cycles of inflated promises, and some introductions into schools, followed by failures. We need to be aware that each system is characterized by structure and function. One without the other is incomplete and cannot be conceived. Thus, it seems that the primary problem of the technology-oriented approach is that it remains inconceivable, that technology remains self-serving, mostly because it considers neither the teacher nor the student; it is not concerned with its actual purpose or the goals of education, and it “demands” that students and teachers adjust to this technology instead of the technology adjusting to their needs.

On the other side, in the learning-oriented approach, we focus first on how people learn, and we perceive technology merely as an aid to and as a tool for learning. Therefore, it seems that technology must be adapted to the needs of both students and teachers in order to create suitable methods for working with it and a suitable pedagogical approach (innovative one-to-one pedagogy) (Aberšek, Borštner, & Bregant, 2014). In short, the majority of yesterday's optimistic forecasts about the influence of educational technology on education have not come true. Taking into account these previous disappointments, in teaching with technology we must strive for an approach aimed towards the students; moreover, the student and his experience need to be placed at the center of the educational process (Dumont et al., 2010). In short, we can agree that in traditional methods of e-learning (in the technology-oriented approach), the individuality of the student is omitted (Dolenc & Aberšek, 2015). The majority of traditional e-material does not consider the varied parameters that influence the learning and learning habits of the individual; because of this, students cannot influence the course of their own learning (Picciano, Saba, as cited in Dolenc & Aberšek, 2015). Autonomous Intelligent and Adaptive E-learning Systems (AIAES) are a generation of new learning systems that include the individuality and personality of the student in the learning process, similar to what happens in a traditional individualized lesson with one teacher and one student. This traditional human tutoring process has proven successful and has represented the most efficient method of learning and teaching since the beginning of teaching.

Fletcher's study has provided some reference points for all future research that deals with evaluating the effectiveness of e-learning systems (Fletcher, 2003). On the basis of meta-analysis of research from this field, he classified and calculated effect size for different e-learning systems. For calculating an e-learning system's effectiveness, he used the distribution theory of the Glass estimator of effect size. The results of Fletcher's research show that modern Autonomous Intelligent and Adaptive E-learning Systems are around 1.05 sigma better than conventional classroom teaching, which however, is still less than 2 sigma, the difference that Bloom measured between tutorial instruction (one-to-one tutoring) and conventional classroom teaching. This difference of 2 sigma (2 standard deviations) was the foundation for all subsequent research in the field of e-learning. An important study in this field was done by VanLehn (VanLehn, 2011), who compared a human tutor, his intelligent learning system and conventional classroom teaching. For calculating effect sizes, he used Cohen's estimator of effect size. VanLehn's study did not confirm such a difference between human tutoring and conventional classroom teaching as did the Bloom study. The effect size of human tutoring compared to conventional classroom teaching was only $d = 0.79$, and his intelligent learning system achieved an effect size of d = 0.76, which is almost as effective as human teaching.

Developing AIAES is connected to varied fields, because a correct and therefore successful implementation of a human teacher, needs to link different fields, from cognitive sciences, artificial intelligence and functional literacy, to many fields connected to education. Computer systems such as ITS should provide the same instructional advantages as a human tutor (teacher), which certainly implies the interdisciplinarity of these fields. Within AIAES, the content is in accordance with the cognitive learning approach, and the system provides services for intelligent analysis (collection of various variables and metadata), which enables machine learning and adaptability to a learning course, based on the learner's individual characteristics and ability during the learning process. The results of the latest meta analysis of effectiveness in such intelligent learning systems (Ma, Adeosope, Nesbit, & Liu, 2014) support the claim that AIAES can be an effective tool for learning in all levels of school.

3 Design of an Autonomous, Intelligent and Adaptive E-learning System with assignments, tasks and exercises

The main objective of the AIAES is to establish an intelligent e-learning environment providing advanced services for the educational process, which will be able to adapt based on a student's learning experience, learning style, cognitive level and personal preferences. The AIAES will be focused on understanding learners' learning styles and cognitive capabilities, putting students and their learning experience at the centre of the educational process (Dumont, Istance, & Benavides, 2010). Based on data gathered, the AIAES will be able to adapt the study course based on a learner's individual characteristics and abilities in the learning process, simulating the traditional individualized lesson with one teacher and one student, which is one of the most efficient methods of learning and teaching (Dolenc & Aberšek, 2015).

The AIAES system should provide e-learning services (see **Pogreška! Izvor reference nije pronađen.**) for both educators and students. Educators can use the system for creating and managing online courses, learning materials (content and tasks), and metadata, together with the rules needed for adjusting the difficulty of the learning content for students based on their achievements while performing learning tasks. The AIAES system should assist educators in planning and creating learning materials, in providing information about reading strategies and functional literacy, and should serve as a validation service for checking e-materials created by educators. The validation services should evaluate attributes such as text length, organization and structure preparation and validation of learning materials, data aggregation and visualization, intelligent instructor services, and metadata (Figure 1).

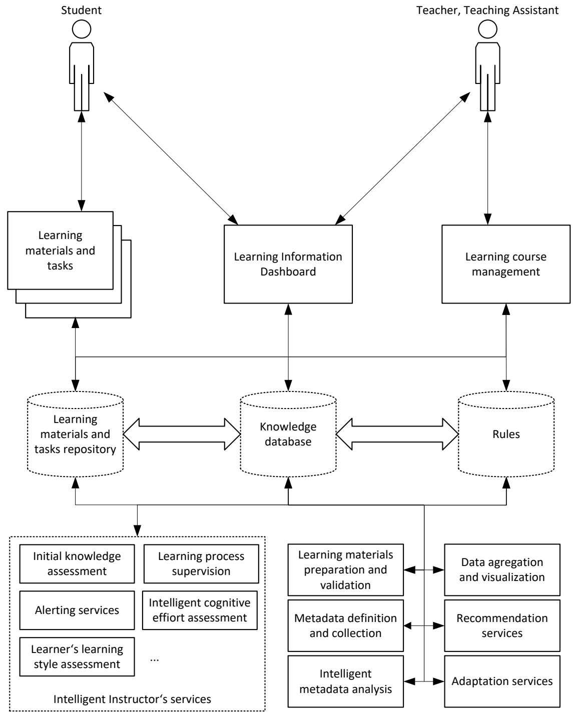

Figure 1. Design of an Autonomous, Intelligent and Adaptive E-learning System with assignments, tasks and exercises

Technically, the first part of the system should be designed as a rule-based adaptive expert system, using production rules for storing expertise and automatically making inferences about the type and level of content and tasks to be communicated to the learners. The second part of the system should collect learners' metadata (results from the learners while using the content and solving the tasks), and perform collective data analysis using machine learning algorithms in order to automatically assess a learner's progress and predict the type of content and tasks to be given to the learner in order to achieve the best possible progress.

In order to support the cognitive learning approach, the AIAES system should provide several features and characteristics, which can be divided into the following services:

1. Intelligent instructor services
2. Services for students
3. Services for educators
4. Domain-based (educational) services
5. Interface services

3.1 Intelligent instructor services

The AIAES will provide advanced services, which will help the learner to consume learning materials and learn based on the results of intelligent assessment. Based on intelligent analysis of the data gathered during the learning process, the AIAES must be able to perform actions and make decisions related to various pedagogical aspects of learning:

1. choosing teaching methods that best suit the individual student's profile,
2. choosing learning content most appropriate for the individual student's profile,
3. choosing and recommending the time when learning content should be studied,
4. assessment of the cognitive state of the student,
5. deciding whether an individual student is able to proceed to the next learning level,
6. indicative, formative and summative testing and evaluation of outcomes.

The AIAES has to provide the same instructional advantages as a human instructor. The traditional human tutoring process has proven successful and has represented one of the most efficient methods of learning and teaching since the beginning of teaching. In order to include and enable the individualization and personalization of the student in the learning process, similar to what happens in a traditional individualized lesson with one teacher and one student, an intelligent instructor will be developed. The design and implementation of an intelligent instructor implies interdisciplinary work between many fields, such as cognitive science, artificial intelligence and functional literacy connected to education. To enable an intelligent instructor within the AIAES, various services will be modelled and implemented, as follows:

1. - Services for initial analysis and assessment of the learner's cognitive abilities and knowledge. Based on initial assessment and classification, the system will be able to provide appropriate study materials. The assessment of the learner's cognitive abilities and knowledge should be repeated within different phases of the learning process in order to evaluate the learner's progress and to be able to make decisions about future actions related to education.
2. - Services for supervision during the learner's studying process - assessment of how much time the learner needs to read the study materials, the amount of content that the learner reads, checking whether the learner has read the full content, checking if questions have been read fully and understood by the learner, checking if the learner is taking enough time to answer individual questions, etc.
3. - Services for collecting metadata gathered during the supervision
4. - Services for alerting the learner
5. - Services for advising the learner
6. - Services for intelligent assessment of the learner's cognitive effort during the learning process
7. - Services for assessment of the learner's learning style – the AIAES system should collect and analyze metadata about learner perceptions, processing and understanding during the learning process.

3.2 Services for students

The idea of adaptive learning is that there exists no one learning style that fits the needs of all types of learners (Yaghmaie & Bahreininejad, 2011). In the existing literature, several learning adaptation approaches have been introduced, such as (1) adaptability based on knowledge about the learner, controlled by the system and (2) student-controlled adaptability based on user preferences. The learning process should be fully adaptable in accordance with the learner's cognitive level, learning style and various preferences (e.g. of device, which can be a desktop computer, laptop, tablet PC, smart phone, etc.). In order to be able to make the AIAES adaptive, the AIAES must provide services for managing the cognitive state of a student. The student's cognitive state must be linked to the student's profile with information such as the student's personal data, learning style and preferences and current level of knowledge. The student's learning style is one of the most important factors in adaptation, since it reflects the learner's characteristics, preferences and needs (Yaghmaie & Bahreininejad, 2011). Based on the student profile, the AIAES should provide services to help the learner process learning materials based on the intelligent assessment of various metadata collected using quantitative and qualitative methods during the learning process.

The system should provide several services for intelligent analysis of data gathered during the different learning phases. These services should provide assessment of the learner's learning capacity, cognitive level, current knowledge and learning style. Based on these assessments, the system should recommend the most appropriate learning content. Additionally, the system should be able to assess the learner's emotional state (e.g. based on keystroke dynamics and mouse movements (Kolakowska, 2013), facial expression analysis, eye-tracking, etc.), which can lead to further adaptation of the learning process, motivating the learner to stay focused on the content.

3.3 Services for educators

The AIAES should be used in two ways. The primary idea is for it to be used as an individual learning tool. However, one potential idea, not yet tested, is for it to be used as a background for learning scaffolded by teachers. Because the system is planned to be launched under a CC licence, it must allow design of content by enthusiastic teachers. Therefore, content prepared by the educators should enable guidance of the learner according to current knowledge and learning capacity. The AIAES system should provide services for preparing the learning materials in an appropriate structure, which can be used for aggregation and presentation to the learners in the learning process according to their given level of learning capacity. Based on the prepared learning content and metadata collected about the learners' status, an information dashboard should be designed to provide important data aggregations in the form of visual analytics (Podgorelec & Kuhar, 2011). The aim of such an information dashboard is the perpetual monitoring of progress in both single learners and learner groups, in order to enable educators to make intelligent predictions and take timely actions, as well as allowing the intelligent instructor to adapt its course of action.

3.4 Domain-based (educational) services

The AIAES should also enable adaptability of the learning content. In the existing literature, there are two general approaches for adapting learning content (Yaghmaie & Bahreininejad, 2011): (1) adaptation of learning content according to individual needs, which is referred to as adaptation in content level, and (2) adaptation of learning content based on learner needs, which is called link-level adaptation. The AIAES must be able to organize learning content based on accepted standards, which were designed and developed to enable sharing and reusing learning content between different learning platforms by providing reusability, durability, accessibility, interoperability, etc. One of these standards is the Sharable Content Object Reference Model (SCORM); however, the SCORM enables only instructor-based adaptation of learning content.

Knowledge about the domain (expertise) is a key area in intelligent behaviour of the AIAES in order to enable intelligent adaption of the content and manner of presentation of certain topics based on learner abilities. Ontology is one technique that will be considered in designing and formalizing knowledge in the AIAES. Ontological description of the domain knowledge provides formalization of declarative knowledge, which can be achieved using various tools that support working with concepts and relations (Grubišić, Stankov, & Peraić, 2013).

3.5 Interface services and other technologies

The AIAES interfaces should be fully adaptable in accordance with learner preferences (e.g. a device, which can be a desktop computer, laptop, tablet PC, smart phone, etc.). The system should be based on modern web technology providing users access to the learning environment on any device (e.g. desktop/laptop computer, tablet PC, smart phone, etc.). Numerous, pre-existing open source online classroom platforms can serve as a basis for development in this project. In particular, Moodle is one of the most widely used such platforms and provides for extensive plugin capabilities. In this case, the PHP programming language should be used. There are no modules so far allowing Moodle or any other online classroom platform to utilize artificial intelligence for student and teacher activities, so this is the part that would have to be developed from scratch. Wenger (Wenger, 2014) suggests multiple approaches to integrating artificial intelligence into a tutoring system. Butler et. al. (Butler, Marsh, Slavinsky, & Baraniuk, 2014) also researched the integration of machine learning methods in STEM classrooms. Kloft et. al. (Kloft, Stiehler, Zheng, & Pinkwart, 2014) used machine learning in MOOC to predict student dropout rates. All these and numerous other studies in combining machine learning with the learning environment will be used to determine the usefulness of integration of these two paradigms and to choose the right method for implementation in the online classroom platform of eventual choosing. The most obvious usage is in predicting the dropout rate with various classification methods, such as statistical methods (naïve Bayes (John, Langley, 1995), logistical regression (Velez, et. al. 2007)), k nearest neighbours (Aha, Kibler, & Albert, 1991), SVM algorithms (Vapnik, 2011), decision trees (Quinlan, 2014) and neural networks (Haykin, 2001). In addition, the same classification algorithms could be used to determine whether a student is ready to proceed through the course and to customize the pace of the learning experience to each student individually.

4 Conclusions

At this point development of AIAES is still in its exploratory phase, and can be regarded as work in progress. Because of vivid progress, both in hardware and software design, applied solutions should be robust and adaptable to new, at this point, unknown technologies. According to planned continuous testing, in both system performance and feedback concerning the suitability of tasks and tests, some of the proposed solutions can be changed, adapted or even abandoned in some situations and added in others. Thus, we plan to design and implement the AIAES in such a manner that will allow agile customization and efficient technological upgrades, without losing the main focus

– a seamless adaptive system for supporting a personalized learning and the improvement of information literacy.

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