Adaptivity and Personalization in Learning Systems based on Students' Characteristics and Context

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***Abstract*— Providing learners with personalized recommendations and/or adaptive courses that fit their characteristics and situation has high potential to make online and mobile learning easier and more effective for learners. However, most of the learning systems that are currently used by educational institutions do not provide adaptivity based on learners' characteristics, needs or situation. In this paper, we introduce our research on considering different learner characteristics and their context in learning systems and therefore provide learners with personalized learning experiences.**

Keywords- adaptivity and personalization; learning styles; affective states; cognitive traits; motivational aspects; context and environment

I. INTRODUCTION

Online learning is becoming increasingly popular and more and more learners learn by using educational technologies. These learners have different characteristics, such as different prior knowledge, learning styles, cognitive abilities, motivation, and affective states, and they learn in different situations/contexts, such as from different devices with different features and functionalities, at different locations and so on. However, when looking at the learning systems that are most commonly used in technology enhanced learning, so-called learning management systems (LMS), it can be seen that these learning management systems typically provide exactly the same course for every learner without consideration of the learners' individual characteristics, situation, and needs. Such a one-size-fits-all approach often leads to frustration, difficulties in learning and a high drop-out rate in online courses [1, 2].

Adaptive learning technologies address this issue and extend learning technologies and systems by enabling them to automatically adapt courses, learning material and/or learning activities to the learners' individual situation, characteristics and needs, and therefore provide learners with personalized learning experiences. By considering the individual differences of learners and their learning situations, adaptive learning systems aim at increasing learners' progress and outcome, enabling learners to learn with less effort, for example, in terms of time required for learning, and offering higher learner satisfaction. By taking into account the learners' differences, a system can, for example, adapt learning material/activities to a learner's prior knowledge [e.g., 3, 4], preferred learning style [e.g., 5, 6, 7], affective states [e.g., 8, 9], and so on. Furthermore, a system can take advantage of surrounding objects or people who might be able to help in the learning process [e.g., 10, 11] and consider the characteristics of the learner's environment as well as the features of the device a learner is using [e.g., 12].

In our research, we particularly focus on six characteristics of learners: the learning styles, cognitive traits, affective states, motivational aspects, and the context/environment of learners. In the following sections, a brief overview of our research works in each of these areas is presented, followed by future research directions.

II. LEARNING STYLES

Research about considering learning styles in technology enhanced learning is motivated by educational and psychological theories, which argue that learners have different ways in which they prefer to learn. Based on these theoretical theories/arguments, several adaptive learning systems have been developed over the last years. Examples of such systems include CS383 [13], WELSA [14], and TSAL [5]. Evaluations of these systems demonstrated the possible benefits of considering learning styles in learning systems, showing that the required time for learning can be decreased and the overall learner satisfaction can be increased. Although these adaptive systems seem to support learners very well, and therefore demonstrate that considering learning styles can help learners in learning, the systems which are currently used by most educational institutions typically do not consider individual differences and in particular do not consider learning styles.

In this section, we demonstrate approaches and mechanisms for enhancing existing (and commonly used) learning systems by enabling them, on one hand, to identify learning styles and, on the other hand, to provide adaptive and personalized courses and/or recommendations to learners once their learning styles have been identified. These approaches and mechanisms are based on the Felder-Silverman learning style model (FSLSM) [15], which proposes that each learner has a preference for each of its four dimensions: the active/reflective, sensing/intuitive, visual/verbal, and sequential/global dimension.

A. *Automatic and Dynamic Student Modelling of Learning Styles*

Student modelling is a crucial part of any adaptive system, dealing with identifying and frequently updating information about a learner which is then used to provide adaptivity. One of our core research contributions in student modelling deals with the automatic identification of learners' learning styles based on the continuous observation of their interactions with the system. This approach is more accurate than the use of simple questionnaires because it can: (1) collect and process data from the learners over a certain period of time; (2) identify and exclude exceptional behaviour; and (3) take dynamic aspects such as changes in learning styles into account. The accurate identification of learning styles facilitates adaptivity and personalization for learners. Therefore, we developed and evaluated a rule-based algorithm that identifies learning styles from the mining of learners' behaviour by observing their interactions with a learning system [16]. The algorithm uses data from 27 behaviour patterns which are based on commonly used types of learning objects and behaviour in an online course. We successfully empirically evaluated our algorithm with 75 students in a course about Object Oriented Modelling presented in the learning management system Moodle, which demonstrates that the algorithm reliably identifies learners' learning styles. Based on the successful evaluation, a stand-alone tool has been developed that accesses the database of a learning system, extracts data from it, and applies the algorithm on these data.

In recent years, more and more research groups started to work on this topic. However, most of the other works aim at identifying learning styles in particular learning systems and therefore are tailored exactly to these systems by using only those behaviour patterns which are incorporated in the respective systems. Moreover, the investigated courses are created in consideration of learning styles by using particular types of learning objects for detecting learning styles. On the other hand, our algorithm and tool uses a generic approach for automatic student modelling, which can be used for different learning systems and courses, aiming at extending existing learning systems.

Furthermore, we investigated the use of dynamic student modelling, where students' interactions with the system are continuously monitored and students' learning styles are updated in real-time. In order to consider dynamic student modelling in learning systems, an architecture has been designed that aims at enabling existing learning systems to build and frequently update learners' learning styles based on FSLSM. Therefore, learners' actions in the learning system are monitored and once a learner performed a pre-defined amount of actions, his/her learning styles are re-calculated through automatic student modelling based on his/her recent behaviour. After this recalculation of learning styles, the result is analysed in the context of the currently stored learning styles of a learner as well as the results of previous re-calculations. For deciding whether an update of learners' learning styles is required, a mathematical model has been designed and verified [17].

Current and future research in this direction deals with investigating the use of artificial intelligence techniques, in particular neural networks and particle swarm optimization, to improve the performance of our student modelling algorithm. Furthermore, we look into expanding the developed tool to not only calculate learning styles but also provide teachers with valuable information about their students' learning styles and how well the learning objects in the course fit the learning styles of the current cohort of students, as well as provide recommendations to teachers on how to improve their courses respectively.

B. *Adaptive Course Provision based on Learning Styles*

In order to use the information about students' learning styles, an adaptive mechanism has been developed and evaluated that enables LMSs to recommend appropriate course structures to learners based on their learning styles [C8]. This adaptive mechanism is a pluggable software package that can be plugged into one of the most widely used LMS, i.e., Moodle, with a very large audience all over the world. The mechanism was used to perform an empirical evaluation based on a target audience of 437 students. The results of our extensive empirical evaluation have revealed that adaptivity in the course structure and presentation can significantly reduce learning time. Based on our observations, a generic framework together with a set of algorithms were developed to extend the adaptive mechanism to be more generic and applicable for different types of courses, such as courses with practical and theoretical focus [18]. This extended adaptive mechanism was used within controlled empirical studies to teach a pilot introductory course on Computing and Information Systems at AU for students from two Alberta School Districts. The developed mechanism advances the field of user adaptive learning systems by providing a concept as well as its implementation on how these systems can adapt to learners' learning styles. This mechanism has been and is planned to be deployed at major educational institutes in three different countries, namely Vienna University of Technology (Austria), Athabasca University (Canada), Alberta Distance Learning Centre (Canada), University of West Indies (Trinidad and Tobago).

Our current and future research in this area deals with combining the adaptive mechanism with automatic and dynamic student modelling. Furthermore, we look into extending the adaptive mechanism to also consider other characteristics of students when providing adaptive courses. In addition, we look into providing adaptive courses in mobile environments.

III. Cognitive Traits

Humans have a number of cognitive abilities. Several of these abilities are crucial for learning. These include abilities such as working memory capacity, inductive reasoning ability, information processing speed, associative learning skills, meta-cognitive skills, observation ability, analysis ability, abstraction ability, and so on.

In our research we mainly focused on investigating the relationship between cognitive traits and learning styles, in order to improve the student modelling process of both through getting additional data from other sources. First, a comprehensive literature review was conducted, followed by an experimental study with 39 students, and then, since both results were promising, a main study with 297 students was conducted [19, 20]. The results of these experiments and detailed analysis showed that relationships exist between working memory capacity and three of the four dimensions of the learning style model. The identified relationships showed high potential to improve the student modelling process of cognitive abilities and learning styles and encourage further research on relationships between learning styles and other cognitive abilities. Furthermore, future research is planned on automatic and dynamic student modelling of cognitive traits from behaviour patterns in online courses as well as the usage of information about learners' cognitive traits to provide them with adaptive courses.

IV. Affective States

Another aspect that can influence the learning process of learners is their affective states. Affective states that are considered to be especially relevant in the learning process include, for example, boredom, confusion, frustration, confidence, satisfaction, and independence.

In our research, we proposed a framework consisting of several modules which aim at incorporating learning styles and affective states, including confidence, effort, independence, and confusion, into learning management systems [21]. Once negative affective states are determined, the system provides a learner with additional elements to guide him/her, considering his/her learning styles in order to determine which additional elements are most helpful.

Future research deals with the extension of the adaptive set of rules as well as the investigation of additional affective states.

V. Motivational Aspects

Motivation is a key factor in education. While there exist some learning system that consider techniques for motivating learners, these systems implement only one or few techniques and assume that the respective technique(s) work well for all learners. However, learners are motivated differently and what is motivating for one learner can be demotivating for another learner.

Our research in this area aims at developing mechanisms and algorithms that provide learners with motivational techniques that work well for them in their current situation. As a first step toward this goal, we introduced a framework of motivational techniques, which suggests motivational techniques that can be included in learning systems, discusses the relationships between these techniques, situations where the techniques might be demotivational for learners, and requirements of the techniques to be integrated into a course and learning system [22]. This framework aims at providing guidelines on how to implement a set of motivational techniques into learning systems and is the basis for providing personalization based on motivational aspects in learning systems.

Our current and future research in this area deals with implementing the proposed motivational techniques as well as investigations and the design of mechanisms and algorithms that provide learners with personalized motivational techniques.

VI. Context and Environment

Due to the recent advances in mobile technologies, learning can take place anytime and anywhere, using not only desktop-computes but also mobile devices such as smart phones and tablets for learning. The learners' current context/situation as well as the characteristics of the surrounding environment in which a learner learns become therefore part of another important aspect to be considered by adaptive technologies. By incorporating information about the context and environment of the learner into the adaptation process, new possibilities for providing adaptivity open up.

In our current research, we aim at enabling mobile systems to "know" the learners' environment and provide him/her with learning objects/activities that work best in such environments. Current investigations deal with the use of different sensors of a mobile phone in order to build a comprehensive student/context model, including for example, whether a learner is in a silent or noisy environment, whether a learner is alone or in a group, whether a learner is at a particular place or moving (e.g., in a bus), etc. Future research deals with using this information to provide learners with adaptive recommendations based on his/her context.

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