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ADAPTATION OF EDUCATION AND LEARNER CONTROL: A MODEL FOR PERSONALIZED TASK SELECTION.

Abstract. The increasing use of authentic tasks in modern instructional design as a principal learning condition results in an augment of task complexity, which may cause cognitive overload, especially in novices in the domain. Completion problems have proven to be efficient by adapting the provided support to the level of expertise of the learner, that is, personalizing instruction. Furthermore, perceived learner control influences motivation positively, affecting also the amount of invested learner effort to perform the learning task. A model is proposed that combines both adaptation and provision of –limited- learner control in order to make instruction more efficient, effective and motivating for students.

1. INTRODUCTION

In recent instructional theories, authentic learning tasks are gaining importance as a driving force for learning. Problems based on real-life situations help learners to integrate the knowledge, skills and attitudes necessary for effective task performance; give them the opportunity to learn to coordinate constituent skills that make up complex task performance, and eventually enable them to transfer what is learned to their daily life or work settings (Reigeluth, 1999; Van Merriënboer & Kirschner, 2001). However, authentic learning tasks which have a high task complexity might cause cognitive overload, especially in novice learners because of the limited capacity of working memory (Baddeley, 1992; Sweller, 1988; Sweller, Van Merriënboer, & Paas, 1998). Therefore, instructional design must not use highly complex learning tasks right from the start of a curriculum because an excessive cognitive load on the learners' cognitive capacity, hampers learning (Sweller, Van Merriënboer, & Paas, 1998). The learning tasks should fit the learner and task selection should depend on the learner' level of expertise.

Cognitive overload could be avoided by using completion problems (Van Merriënboer, 1997). Problem solving can be explained as a search of a set of operators (or a solution) that links a given state to a goal state (Newell & Simon, 1972). This search involves returning to prior knowledge (schemas) to recognize the problem. If a related schema already exists, it must be induced, if not, instructional design should help acquire it. In completion problems, learners start to work on case studies that confront them not only with a given-problem state and a desired-goal state, but also with a partial solution. Completion problems help learners to focus on the problem state and its associated set of operators. According to cognitive load theory, this kind of delayed problem solving may prevent extraneous cognitive load and moreover it directs learners' attention to processes relevant for learning, hereby enhancing germane cognitive load and facilitating problem solving and transfer performance. Completion problems (i.e., tasks with medium support) provide a bridge between worked out examples (i.e., tasks with a full solution and thus with full support) and conventional problems (i.e., tasks without support). In line with this idea, Renkl and Atkinson (2003) propose a progressive fading-out strategy of worked-out examples in problem-solving.

To provide each learner with a type of learning task (i.e., worked-out example, completion problem, or conventional problem), or the amount of support (i.e., full, medium, or none) appropriate for his or her level of expertise, the learning environment should adapt instruction. Human tutoring is most likely the oldest form of individualized instruction. It provides highly interactive, personal feedback to support students' problem solving (Merrill, Reiser, Ranney, & Trafton, 1992). Intelligent tutoring systems (ITS), which are problem-solving environments, have been recognized by artificial intelligence researchers as rich environments that capture some benefits of human tutors in computer-based tutoring systems (Corbett, Koedinger, & Hadley, 2001). Since then, such computer-based programs, gradually increased personalization of the instructional material (for a review see Salden, Paas, & Van Merriënboer, 2003). Especially with the introduction of *dynamic* whole-task approaches, it is possible to adapt instruction during training based on a learners' performance. From a learner-centered perspective, adaptation seeks to take into account the special needs of learners (Brna & Cox, 1998). Instruction should start with the assumption that for every learner, it is critical to determine the right amount and type of support and to fade this support at the appropriate time and rate. This in order to avoid excessive or insufficient support which may hamper the learning process (Van Merriënboer, Kirschner & Kester, 2003). An example of an electronic learning environment that allows for individualization is Completion Assignment Constructor (CASCO) described by Van Merriënboer and Luursema, (1996). It is an ITS for teaching computer programming. CASCO's decisions are made based on a learner profile and presentation selection rules. In this way, the dynamic task selection model prioritises learning tasks for each specific student, that is, adapting instruction.

Besides individualization of instruction another important aspect of task selection is learner control. There is strong evidence that as levels of expertise increase, it is appropriate to decrease instructor control and increase learner control (Niemiec, Sikorski, & Walberg, 1996). Effective instruction provides novice learners with guidance as a substitute of inadequate schemas associated with a learning task. Experts have adequate schemas and therefore such guidance may be not necessary and even redundant (Kalyuga, Ayres, Chandler, & Sweller, 2003). So, to avoid redundancy, more experienced learners should have more control over task selection. Allowing people to choose which tasks to work on facilitates the intention to continue and improves motivation (Reeve, Hamm, & Nix, 2003), and moreover, motivation, determines amongst others the amount of mental effort invested during learning. Invested mental effort is strongly related to performance (Paas & Van Merriënboer, 1994). Learners in control will perceive more self-efficacy in performing such tasks, which will affect motivation positively (Keller, 1983).

Academic success depends to a substantial extent not only of student's motivation and adequate and extensive practice, but also of his or her use of self-regulatory processes (Zimmerman, 2002). It is assumed that personalized task selection that allows learner control positively influences effectiveness, efficiency, and motivation.

2. THE EXPERIMENT

To investigate whether adaptation of instruction with –limited- learner control over task selection makes instructional design more efficient, effective, and motivating for the learner, a personalized and dynamic task selection model will be developed.

2.1. Participants

The experiment will be conducted in levels 3 and(/or) 4 of secondary vocational education in the Netherlands in a technical domain. In this experiment, at least 80 participants will participate.

2.2. Design

The task selection model will be tested in a 2x2 factorial experiment with two factors: Adaptation (adapted selection based on a learner profile vs. yoked control). In the yoked control condition, each student will receive the same learning tasks than a peer of the adapted condition, so not based on his/her own learner profile. The second factor is selection control (system control vs. limited learner control). For system control, one task is selected by the system and presented to the student, who may work on this task at his or her own pace; for limited learner control, a shortlist of tasks is selected and the learner may select one task from this shortlist. This way, from a learner-centred approach perspective, the learning problems picked up by the system will fit students' needs (since decision-making is individualized based on the learner profile) and interests (since limited learner control lets the student make the final decision).

2.3. The learning environment

The learning environment contains learner profiles and offers facilities for performance assessment, in order to update the learner profiles and then select a subsequent learning task for each individual student.

The learner profile consists of information of the prior knowledge of the student, the amount of invested mental effort on each learning task, and performance measures. Performance measures are based on test tasks after each learning task consisting of tasks without support. The level of expertise and competence will be determined. The task selection model, based on the learner profile, will select a range of suitable tasks (e.g., 4-7) from a learning-tasks database. This range of most suitable subsequent learning tasks will be presented to the learner, which will be provided with a limited learner control. The learner will make the final selection. After performing the learning task at his or her own pace, the level of competency and expertise, as well as the mental effort will be assessed in order to update the learner profile. This updated learner profile will be used as a basis for the next learning-task selection. In this way, after each learning task, the learner profile will be automatically updated.

2.4 Hypotheses

It is hypothesized that a dynamic and personalized task selection model provides a more efficient, effective and motivating instruction for the learner. Adaptation of instruction (by providing higher support in early stages of instruction, and reducing this support as level of expertise increases), combined with provided limited learner control over task selection, implemented in an electronic learning environment, will make instruction more efficient, effective and motivating than the other three experimental conditions.

AFFILIATION

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