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The influence of student characteristics on the use of adaptive e-learning material

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ABSTRACT

Adaptive e-learning materials can help teachers to educate heterogeneous student groups. This study provides empirical data about the way academic students differ in their learning when using adaptive e-learning materials. Ninety-four students participated in the study. We determined characteristics in a heterogeneous student group by collecting demographic data and measuring motivation and prior knowledge. We also measured the learning paths students followed and learning strategies they used when working with adaptive e-learning material in a molecular biology course. We then combined these data to study if and how student characteristics relate to the learning paths and strategies they used. We observed that students did follow different learning paths. Gender did not have an effect, but (mainly Dutch) BSc students differed from (international) MSc students in the intrinsic motivation they had and the learning paths and strategies they followed when using the adaptive e-learning material.

1. Introduction

The variety in prior knowledge within student groups has increased since the Bachelor/Master system was introduced at European universities in order to increase student mobility within the EU. Students enrolling in Master's programmes come from different universities and their knowledge on specific topics varies. These varying backgrounds mean that university staff must provide the students with intensive tutoring. Time-consuming tutoring can be supported by adaptive e-learning material. Adaptive e-learning is suitable for teaching heterogeneous student populations in higher education (Schiaffino, Garcia, & Amandi, 2008), as it addresses the variety in the prior knowledge of students who enrol in a course. This gives students the opportunity to follow individual learning paths and meet their specific training needs (Brusilovsky, Eklund, & Schwarz, 1998).

Although several studies report on the benefits of adaptive e-learning (see for example Armani, 2005; Melis et al., 2001; Virvou & Tsiriga, 2001), there is little to no empirical evidence that students do follow individual learning paths associated with their differences in prior knowledge. It is also unknown whether other student characteristics such as gender or intrinsic motivation influence their learning paths. Since the development costs of computer-based learning environments (CBLEs) are high, it is important to know under what circumstances and for which student groups adaptive e-learning is effective. This study provides empirical evidence to support educators' decisions. As such, it links up with questions raised by, for instance, Narciss, Proske, and Koerndle (2007) at the end of their manuscript: 'To date there has been little research into how individual differences in problem-solving strategies and styles, students' goals and motivational orientations and students' meta-cognitive skills contribute to differences in studying in web-based learning environments. … An… issue for future research and practice is the question how individual variables may determine the way students learn with web-based learning environments'. (p. 1141)

In addition to these practical aims, research into computer-based learning can provide more insight into the ways students self-regulate their learning. As Winne (2010) has pointed out: 'widespread use of CBLEs is vital to significantly accelerating the science of learning, particularly regarding self-regulated learning (SRL), and applying its findings in education.' (p.267) Azevedo, Moos, Johnson, and Chauncey (2010) claim that learning in hypermedia environments involves the use of numerous self-regulatory processes, such as planning, knowledge activation, metacognitive monitoring and regulation, and reflection. We think that this claim can be extended to other CBLEs and

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that adaptive e-learning material is a good tool to investigate SRL. This study therefore paid special attention to the SRL strategies that students adopt when using adaptive e-learning material.

1.1. Adaptive e-learning

E-learning is defined by Shute and Towle (2003) as 'learning that takes place in front of a computer that is connected to the Internet' (p. 106). Adaptive e-learning is generally perceived from the instruction point of view and comprises CBLEs that can interact with a student to provide the most appropriate instruction. Thus, it is not students' learning that adapts, but the instruction provided by the system. Adaptive e-learning is currently applied to improve the instruction given to heterogeneous student groups (Brusilovsky et al., 1998; Van Seters, Ossevoort, Goedhart, & Tramper, 2011).

Adaptive e-learning material has been investigated by multiple disciplines, including educational psychology and computer science, and each discipline uses its own terminology to label similar concepts. Adaptive e-learning systems consist of multiple components that together enable instruction that is tailored to the needs of the individual students. The names of the components, according to the terms used in educational psychology (with those from computer science given between brackets), are: the content model (domain model), the learner model (user model), the instruction model (interface model) and the adaptive engine (Brusilovsky, 1996; Shute & Towle, 2003).

The *content model* contains the concepts that a student should master. In educational research, the concepts are usually described as learning objectives, which combine the concepts with the actions that students should be capable of doing, such as remember, understand, apply, etc.

The *learner model* contains information about the individual student, such as preferences for textual or visual information, demographic data such as gender or age, and information about the knowledge of a specific topic. The information in the learner model can be obtained before commencement of the learning activity and does not change during the interaction with the system (static), or it can be updated during the interaction (dynamic) (Brusilovsky, 2001).

The *instruction model* monitors the learner model in relation to the content model in order to ascertain the student's mastery of concepts. As such, the instruction model determines how close a student is to the target competence level after carrying out a learning activity.

The *adaptive engine* is an algorithm that integrates information from the preceding models in order to select appropriate learning content to present to the student.

1.2. Self-regulated learning

Being able to regulate one's own learning is viewed by educational psychologists and policy makers as the key to successful learning at school and beyond. SRL refers to learning situations in which students set their own learning objectives. Students plan, conduct, regulate and evaluate the learning process individually to achieve their objectives. Monitoring and evaluating the learning progress are essential for successful SRL (Narciss et al., 2007). To allow students to reflect on their own learning, they should have control over their learning process. A way to provide self-control is by offering choices (Winne, 1995; Winne & Perry, 2000).

A well-known driving force for SRL is intrinsic motivation. Students who are eager to study a subject and appreciate the learning environment engage more in SRL. In addition, the familiarity that students already have with the subject and the learning environment influences their use of SRL (Winne, 1996). Other factors that influence self-regulated learning are, for instance, demographic characteristics such as culture or gender. Women are reported to score higher than men on help-seeking strategies, utility value and performance anxiety (Virtanen & Nevgi, 2010). Cultural differences have also been reported to influence SRL (Biemans & Van Mil, 2008). In this study, Chinese students are less likely to self-regulate their learning than Dutch students, since the former adopt a reproduction-directed learning style.

In a recent article, Winne (2010) points out the problem of measuring SRL. Commonly used methods are inventories and think-aloud protocols, but these methods have some disadvantages. Inventories gather data after an intervention, relying on the memory of students. Think-aloud protocols alter the learning environment and natural behavior of the student. CBLEs offer an alternative way to measure SRL by logging the student interactions with the system, resulting in reliable data for educational research (Winne, 2010). These 'traces' are gathered during interventions, on the fly and do not intervene with a student's natural behavior.

1.3. Feedback

Feedback is defined as any message that is generated in response to a student's action (Mason & Bruning, 2001). Feedback usually indicates the student's performance in comparison with the expected one (Johnson & Johnson, 1993). By doing so, feedback helps students to identify errors and become aware of misconceptions. Feedback also provides clues about the best approaches to correcting errors (Mason & Bruning, 2001). Good feedback might strengthen the students' capacity to self-regulate their own performance (Nicol & Macfarlane-Dick, 2006) and is therefore an important aspect to take into account when investigating SRL.

Feedback is most effective when it is tailored to individual students and helps them to proceed (Brookhart, 2008). Many types and classifications of feedback have been reported, as has the effectiveness of each type. Feedback can be about the task (FT), the processing of the task (FP), self-regulation (FR) or the self as a person (FS). FT is the most common and is often called corrective feedback or knowledge of results. FT tells a student whether the answer he or she provided is correct or incorrect, such as: 'Your answer is correct, but you have to include more arguments to support your conclusion'. FP is more specific to the learning steps that are needed to perform tasks, such as: 'The order of the calculation steps you made was correct.' FR concerns the feedback students create for themselves. Self-regulation feedback is initiated by the student rather than by the teacher and can prompt the student to look for more information on a certain topic, without specific directions. FS typically expresses positive evaluations, such as 'Well done' or 'Great effort', although it can be negative. It usually contains little task-related information and is rarely converted into more engagement, commitment to the learning goals, enhanced self-efficacy or understanding of the task (Hattie & Timperley, 2007). Feedback on the processing of the task (FP) has been applied to intelligent e-learning by Narciss et al. (2007), which they call informative tutoring feedback. Informative tutoring feedback provides strategically useful information that guides the student step by step towards successful task completion, thereby assisting multiple solution attempts.