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Exploring feedback and student characteristics relevant for personalizing feedback strategies

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ABSTRACT

Personalized tutoring feedback is a powerful method that expert human tutors apply when helping students to optimize their learning. Thus, research on tutoring feedback strategies tailoring feedback according to important factors of the learning process has been recognized as a promising issue in the field of computer-based adaptive educational technologies. Our paper seeks to contribute to this area of research by addressing the following aspects: First, to investigate how students' gender, prior knowledge, and motivational characteristics relate to learning outcomes (knowledge gain and changes in motivation). Second, to investigate the impact of these student characteristics on how tutoring feedback strategies varying in content (procedural vs. conceptual) and specificity (concise hints vs. elaborated explanations) of tutoring feedback messages affect students' learning and motivation. Third, to explore the influence of the feedback parameters and student characteristics on students' immediate post-feedback behaviour (skipping vs. trying to accomplish a task, and failing vs. succeeding in providing a correct answer). To address these issues, detailed log-file analyses of an experimental study have been conducted. In this study, 124 sixth and seventh graders have been exposed to various tutoring feedback strategies while working on multi-trial error correction tasks in the domain of fraction arithmetic. The web-based intelligent learning environment ActiveMath was used to present the fraction tasks and trace students' progress and activities. The results reveal that gender is an important factor for feedback efficiency: Male students achieve significantly lower knowledge gains than female students under all tutoring feedback conditions (particularly, under feedback strategies starting with a conceptual hint). Moreover, perceived competence declines from pre- to post-test significantly more for boys than for girls. Yet, the decline in perceived competence is not accompanied by a decline in intrinsic motivation, which, instead, increases significantly from pre- to post-test. With regard to the post-feedback behaviour, the results indicate that students skip further attempts more frequently after conceptual than after procedural feedback messages.

1. Introduction

Development of personalized learning environments is among the most important research areas of computer-based education for the next decade (Spada et al., 2012; Wolf, 2010). Such environments should be capable of tracing accurately learners' activity, monitor their individual characteristics, and generate timely adaptive interventions according to effective pedagogical strategies. Over the years, many different technologies have been developed for optimizing instructional interventions to the needs, goals, and knowledge of individual

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learners. For example, cognitive tutors rely on rigorous rule-based models of cognitive tasks and step-by-step tracing of students' progress through these tasks in order to provide just-in-time assistance (Anderson, Corbett, Koedinger, & Pelletier, 1995). Constraint-based tutors try to achieve a similar goal by defining the boundaries of correct knowledge in the domain, restricting the possible solution space and reacting when a student's solution violates it (Mitrovic, 2011). Personalized course generation technologies are used to plan sequences of learning objects optimized for individual student's knowledge and learning goals (Brusilovsky & Vassileva, 2003). Tutorial dialogue systems engage in educational conversations with students: They track students' behaviour with the system and use these behavioural traces for monitoring what students know and do not know, and generate dialogue moves that help students to gradually construct their knowledge (Olney, Graesser, & Person, 2010). Adaptive educational hypermedia combines a wide range of techniques in order to tailor the presentation of hypermedia learning content based on student characteristics and navigate students through large corpora of learning documents by generating hyper-links between them and/or decorating these links with personalized cues (Brusilovsky & Henze, 2007).

One more way to organize personalized learning is to provide adaptive formative feedback (Shute & Zapata-Rivera, 2008) or tutoring feedback strategies (Narciss, 2008) to the learners working on exercises. Formative feedback is a key element of formative assessment systems; it provides learners with information about their current state of knowledge in order to improve their learning. Tutoring feedback strategies combine elaborated formative feedback with tutoring and mastery learning strategies. In doing so, they provide such formative feedback that makes learners aware of important gaps existing between their current state of knowledge and their learning goal. Additionally, they provide assistive elaborated feedback (e.g. hints, explanations, and attribute-isolation examples) that is aimed at helping students to detect errors, overcome obstacles, and try more efficient solution paths. In doing so, tutorial feedback strategies offer strategically useful information for task completion without immediately providing the correct solution; they also prompt the learner to apply this information to solve the learning task in the next trial. Furthermore, after successful task completion, they provide confirmatory positive feedback components (cf. Narciss, 2006, 2008, 2012a, 2012b, 2013; Narciss & Huth, 2006). Personalized tutoring feedback has been identified as a very powerful method that expert human tutors apply when helping students to resolve learning difficulties, to monitor their progress, and to optimize the overall learning process (Merrill, Reiser, Ranney, & Trafton, 1992; VanLehn, 2011). Such tailoring of tutoring feedback based on learners' characteristics, and/or parameters of the environments is a promising way to implement adaptive computer-based learning.

Unfortunately, while there is a large body of empirical research on the effectiveness of different types of non-adaptive feedback (Narciss, 2008, 2012, 2013; Hattie & Gan, 2011; Hattie & Timperley, 2007; van der Kleij, Eggen, Timmers, & Veldkamp, 2012; Shute, 2008; Thurlings, Vermeulen, Bastiaens, & Stijnen, 2012), automatic feedback adaptation has received much less attention in empirical and/or theoretical feedback research. Several researchers have suggested frameworks providing guidelines or methods for developing adaptive feedback (Choe, Bae, Kim, & Lee, 2004; Chuang & O'Neil, 2006; Economides, 2006; Gimeno Sanz & De-Siqueira, 2009), yet, these frameworks are only partly rooted in thorough educational theories, and their empirical evaluation with students has been rather scarce. However, a few attempts to implement and test adaptive feedback functionality in a real adaptive educational system (AES) have been made and the results look promising. For example, Vasilyeva and colleagues (Vasilyeva, De Bra, Pechenizkiy, & Puuronen, 2008; Vasilyeva, Pechenizkiy, & De Bra, 2008) as well as Parvez and Blank (2008) have demonstrated the possibility of automatically tailoring instructional feedback to students' learning styles and found a positive effect of adaptive feedback on students' performance. Another study has shown that students themselves believe that adapting feedback may be not needed for successful students, but can be very important if a student is under-achieving (Dennis, Masthoff, & Mellish, 2012). Conati and Manske (2009) investigated adaptive feedback in a serious learning game; their findings indicate that the effectiveness of adaptive feedback can decrease, if it is presented too frequently and provides more information than the learner needs at the moment. Goldin and his colleagues (Goldin, Koedinger, & Aleven, 2012) have data-mined several models measuring individual feedback effectiveness and have found, that for different students the effectiveness of feedback messages varies. This allowed them to conclude that there may be a feedback processing skill or proficiency that depends on the level of details provided by the feedback messages.

These rather mixed results indicate that design and evaluation of adaptive feedback strategies is a challenging task, because so many individual and situational variables can facilitate or hinder the effect of feedback on learning process. Unfortunately, most studies have focused only on one or two of such parameters and investigated their effects mainly on aggregated outcomes (e.g., performance, learning gain). Studies analysing in detail how individual learner and feedback characteristics influence not only the global outcomes, but also more local variables characterizing the immediate effect of feedback on learning process (e.g., post-feedback behaviour) are sparse (Timmers, Broek den, & van den Berg, 2012). Thus, despite the growing attention to feedback-based learning technologies (Author, 2008, 2012, 2013; Hattie & Gan, 2011; van der Kleij et al., 2012; Shute, 2007; Thurlings et al., 2012), many problems in this field remain unresolved. And the big questions, such as "How to design effective tutoring feedback strategies?", "Which factors of learning process should such strategies address in the first place?", and "How these factors influence each other when combined in adaptive feedback components?" have not been answered yet by the research community.

In this paper, we focus on the two latter questions by examining sets of (a) content-related feedback characteristics and (b) learner characteristics influencing learners' problem solving behaviour in computer-based learning tasks supported with tutoring feedback. In many respects, these factors define how students would react to feedback messages and how much they would learn when practicing with an AES providing tutoring feedback, and thus, represent critical information for feedback adaptation. This direction of research is highly important; because even the most thoroughly designed adaptive feedback strategy can be inefficient if students do not use the feedback content in a mindful way in order to improve their learning (see also Timmers et al., 2012). To address these issues, in the remainder of this section, we further synthesize current and past feedback research on the basis of an integrative, multi-dimensional framework for designing and evaluating tutoring feedback strategies (Narciss, 2008, 2012, 2013) and specify our research questions.

1.1. Design of adaptive feedback strategies

In light of recent reviews of feedback research (Narciss, 2008, 2013; Hattie & Gan, 2011; Shute, 2007; Thurlings et al., 2012) and research on computer-based adaptive learning environments (Vandewaetere, Desmet, & Clarebout, 2011), the design and examination of adaptive feedback strategies and, in particular, tutoring feedback strategies require adopting a multidimensional view of feedback. According to Narciss (2012), the nature and quality of a feedback strategy is determined by at least three facets of feedback: