Computers & Education 72 (2014) 196–208

Contents lists available at ScienceDirect

Computers & Education

journal homepage: www.elsevier.com/locate/compedu

University students' achievement goals and help-seeking strategies in an intelligent tutoring system

Bram E. Vaessen [a,*], Frans J. Prins [a], Johan Jeuring [b]

[a] *Social and Behavioural Sciences, Utrecht University, Education Department, P.O. Box 80140, 3508 TC Utrecht, The Netherlands*
[b] *Department of Information and Computing Sciences, Utrecht University, P.O. Box 80.089, 3508 TB Utrecht, The Netherlands*

A R T I C L E I N F O

Article history:
Received 1 May 2013
Received in revised form
30 October 2013
Accepted 6 November 2013

Keywords:
Intelligent tutoring systems
Interactive learning environments
Learning strategies

A B S T R A C T

Help seeking behavior in an intelligent tutoring system was analyzed to identify help seeking strategies, and it was investigated whether the use of these strategies could be predicted by achievement goal scores. Discrete Markov Models and a *k-means* clustering algorithm were used to identify strategies, and logistic regression analyses ($n = 45$) were used to analyze the relation between achievement goals and strategy use. Five strategies were identified, three of which were predicted by achievement goal scores. These strategies were labeled Little Help, Click Through Help, Direct Solution, Step By Step, and Quick Solution. The Click Through Help strategy was predicted by mastery avoidance goals, the Direct Solution strategy was negatively predicted by mastery avoidance goals and positively predicted by performance avoidance goals, and the Quick Solution strategy was negatively predicted by performance approach goals.

1. Introduction

Interactive learning environments (ILEs), which are used to train or teach novices, are becoming more widespread (Koedinger, Anderson, Hadley, & Mark, 1997). Such an environment usually provides on-demand help functionality (Aleven, Stahl, Schworm, Fischer, & Wallace, 2003). In intelligent tutoring systems (ITSs), which are a type of ILE, the help functionality is usually a crucial part of the software as it can help to support a student individually by providing context sensitive hints and feedback. Compared to human tutoring, however, the software-tutor does not have access to verbal and non-verbal forms of communication (Wood & Wood, 1999). This means that ITSs place higher demands on a student's self-regulatory ability, because a student must decide for herself when she needs help and what kind of help she requires. It is, therefore, not surprising that students often do not use such help systems appropriately (Aleven et al., 2003; Beal, Qu, & Lee, 2008).

To improve the value of ITSs by finding ways to stimulate more effective behavior, it is important to find out how a student uses these help systems and what factors influence this behavior (Karabenick, 2011). Currently, there is one model that describes desired help-seeking behavior within an ITS (Aleven, Mclaren, Roll, & Koedinger, 2006), but this model only captures desired versus undesired behavior, and its design was not based on empirical data. We took a more explorative approach to identify different help-seeking strategies within an ITS (based on Köck & Paramythis, 2011). Achievement goals are an important influence on help-seeking behavior in classroom situations, but have not been investigated well in ITSs (Aleven et al., 2003; Huet, Escribe, Dupeyrat, & Sakdavong, 2011). We investigated the relation between the use of help-seeking strategies and students' achievement goals (Elliot & McGregor, 2001), We studied help-seeking strategies in an intelligent tutor for functional programming, in which a student incrementally solves functional programming problems. The tutor gives feedback, hints, and worked-out solutions based on annotated model solutions provided by teachers (Jeuring, Gerdes, & Heeren, 2012).

1.1. Intelligent learning environments and intelligent tutoring systems

An interactive learning environments is a computer-based instructional system that offers a task environment and provides support to help novices learn skills or concepts involved in that task (Aleven et al., 2003). An ITS is a type of ILE that is designed for individual learning,

* Corresponding author. Nolenslaan 53, 3515 VD Utrecht, Netherlands. Tel.: +31 620944065.
E-mail addresses: b.e.vaessen@uu.nl, bram.vaessen@gmail.com (B.E. Vaessen), f.j.prins@uu.nl (F.J. Prins), J.T.Jeuring@uu.nl (J. Jeuring).

0360-1315/$ – see front matter
http://dx.doi.org/10.1016/j.compedu.2013.11.001

and distinguishes itself from other types of ILEs by its ability to model the cognitive state of the user, which allows for context sensitive hints and feedback at all steps of a learning process (e.g. Graesser, Chipman, Haynes, & Olney, 2005; Vanlehn et al., 2005). The advantage of using an ITS over other types of ILEs for *investigating* help-seeking behavior is that information about the cognitive state of the user is available, which may improve the interpretation of the observed help-seeking behavior. Although we studied the use of an ITS in this research, the approach for finding strategies can be used in any ILE that offers help functionality and is able to log user interactions.

1.2. Help seeking in ITSs

Help seeking is conceptualized by Ames and Lau (1982) as "an achievement behavior involving the search for and employment of a strategy to obtain success". Ryan, Pintrich, and Midgley (2001) identified the following steps in the help-seeking process: a) become aware of need of help, b) decide to seek help, c) identify potential helper(s), and d) use strategies to elicit help. In the first step, a student must become aware that the task is too difficult and that she is in need of help. In some situations this might be more difficult than it sounds; meta-cognitive skills such as self-monitoring and evaluation of own skills are required for this step. The next step is also crucial: even if a student acknowledges the need for help, she still has to decide whether she will seek help or not. A student might not seek help because she believes that, even with help, her basic competencies are not sufficient to solve the problem. Or she may have had prior experiences in which seeking help was not successful (Ames & Lau, 1982). Another reason for not seeking help is that a student may perceive seeking help as a threat to self-esteem or a threat to autonomy (Deci & Ryan, 1987; Huet et al., 2011; Karabenick, 2004; Ryan et al., 2001). This means she is either afraid of social embarrassment, or believes she will learn more if she tries without help. The third and fourth step refer to the social aspects of seeking help, and are not considered in this paper.

A differentiation is often made between *executive help seeking* and *instrumental help seeking* (Karabenick, 2004; Nelson-Le Gall, 1981). The goal of executive help seeking is to decrease the cost of completing a task by asking help from others, for example by asking for the answer to a problem. The goal of instrumental help seeking is to get the minimal assistance required to independently complete a task.

Help seeking in ITSs has been studied before (for a review, see Aleven et al., 2003), but not to the same extent as in classroom situations. It is not fully clear how much help seeking in ITSs differs from help seeking in classrooms, but it is often found that students avoid the help functionality, use it ineffectively, or abuse it. This is unfortunate, as appropriate help seeking in an ITS can improve learning. Several personal factors, but also the design of the help functionality, have been found to influence help-seeking behavior.

1.3. Measuring help seeking behavior and help seeking strategies in ITSs

1.3.1. Frequencies versus sequences

One can measure help-seeking behavior in intelligent tutoring systems in several ways. One straightforward approach is to count the number of times a student asks for certain types of help while completing an exercise (Huet et al., 2011; Wood & Wood, 1999). However, only considering the frequency of help seeking does not give enough information, because help seeking is a process, in which the necessity of help and the decision to seek help or not are important (Ryan et al., 2001). Imagine, for instance, an ITS that provides a user with two help buttons for each step; one button provides the user with a hint, the other button presents the answer to the current step. Two attempts at solving an exercise might consist of the following activities:

Student 1: ReqHint → ReqAnswer → TrySuccess → TryFail → TryFail → TrySuccess.
Student 2: TryFail → ReqHint → TryFail → ReqAnswer → TrySuccess → TrySuccess.

The frequencies of the activities of both students are the same, but their help-seeking behavior is rather different. Student 1 started the exercise by requesting a hint, as well as the answer for the first step, and requested no help after a failed attempt on the third step. In comparison, Student 2 only requested a hint after a failed attempt, and only requested an answer when the hint was not helpful. Thus, the sequence of activities can be more informative than the frequency.

Modeling sequences is not as straightforward as counting the frequencies of help requests. One way to quantify help-seeking behavior using sequences is to look for similarities in sequences, and to use these similarities to classify behavior. Köck and Paramythis (2011) modeled and clustered activity sequences to discover and classify help-seeking behavior. Activity sequences were modeled using Discrete Markov Models (DMM), and strategies were identified using a *k*-means clustering algorithm.

1.3.2. Discrete Markov Models and help-seeking behavior

A DMM is a probabilistic model containing a finite number of N states, $N \times N$ transition probabilities, and N initial state probabilities. Each activity the student performs in an ITS is modeled as a state. Furthermore, for each pair of activities (states) a transition probability is calculated, based on sample data. For example, a transition probability of 0.3 for activity A to activity B signifies that if a student performed activity A, there is a 30% chance that the student will then perform activity B. This is valuable information because it can show, for example, how often a student requests an *answer* after a failed attempt compared to how often a student requests a *hint* after a failed attempt. All these transition probabilities taken together can be seen as a model for the student's interactions within an exercise. To only model help-seeking behavior, a subset of transition probabilities is selected. This subset (i.e. the combination of selected transition probabilities) is then considered a model of the help-seeking behavior of a student during an attempt on an exercise.

1.3.3. Clustering and interpreting help-seeking strategies

It is assumed that many help-seeking behaviors are similar, and that several typical *help seeking strategies* can be distinguished when students use the same electronic learning environment. To find these typical strategies, a clustering algorithm is used. Attempts on exercises with similar transition probabilities are grouped into clusters. Because the transition probabilities in a cluster are similar, it is assumed the same help-seeking strategy was used in a cluster. The centers of a cluster, which are averaged transition probabilities, can be interpreted as a help-seeking strategy.