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Abstract

Questionnaires to assess goal orientation are widely used. However, recent research indicates some shortcomings. Most significantly, questionnaire data are unable to capture developments and changes in students´ goal orientation during the learning process. Therefore, it seems appropriate to supplement questionnaire data with online measures that directly tackle students' behavior. We analyzed data of 57 students who participated in a study with the Cognitive Tutor Geometry. Specifically, we analyzed relationships between questionnaire data on goal orientation, the use of hints and a glossary while working with the Tutor as potential online indicators for goal orientation, and learning outcomes. Results of our analyses show that our potential online indicators systematically differ from questionnaire data of goal orientation, yet have high predictive power for learning outcomes. Therefore, online indicators may be used to supplement questionnaire data of goal orientation and/or to further optimize adaptation in intelligent tutoring systems.

Keywords: Motivation, Goal Orientation, Self-regulated Learning, Intelligent Tutoring Systems

Introduction

Motivation and self-regulated learning are inseparably intertwined. One specifically important and well-investigated area of motivation is that of achievement goal theory (Pintrich, 2000). Initially, the theory's basic distinction was between mastery goal and performance goal orientation (e.g., Dweck, 1986). Mastery goal orientation refers to the goal of reaching understanding and mastery in a field. Performance goal orientation refers to the goal to perform better in comparison to others (Elliot & McGregor, 2001). Mastery goal oriented students have often been found to show more effort and persistence during learning and, as a result, better learning outcomes compared to performance goal oriented students (Urdan, 1997). Elliot and McGregor (2001) introduced "valence" as an additional dimension to describe goal orientation; that is, approaching success versus avoiding failure. This additional distinction leads to four aspects of goal orientations: mastery-approach, mastery-avoidance, performance-approach, and performance-avoidance goal orientation.

Initially, goal orientation was regarded as a relatively stable personality trait (e.g., Dweck & Leggett, 1988). Later studies, however, put an emphasis on the influence of situational variables and task characteristics on goal orientation (e.g., Butler, 1993). Some researchers pointed out as early as in the 90s, that students may not clearly belong to one or the other group of learners in classroom situations (i.e., performance versus mastery goal oriented or approach versus avoidance oriented). In contrast, it is highly plausible that students show both mastery and performance goal orientations at the same time, albeit at different levels. Also, there may be variations in the students' predominant goal orientation during learning phases depending on the task at hand and level of expertise (e.g., Meece & Holt, 1993). In analogy to the state-trait concept of anxiety first introduced by Cattell and Scheier (1961), recent research points to the reciprocal influences of state and trait measures in the field of goal orientation (Chen, Gully, Whiteman, & Kilcullen, 2000).

Typically, goal orientation is measured via self-report questionnaires. This approach is rooted in the traditional view of goal orientation as a personality trait and can be considered to measure habitual goal orientation. Despite their long tradition and proven utility in the field, interpretation of questionnaire data of achievement goal orientation can be problematic. More specifically, ambiguity between different questionnaires with respect to their conceptual overlap often makes it difficult to compare findings from different studies (Hulleman, Schrager, Bodmann, & Harackiewicz, 2010). Also, data measured before or after a learning phase using self-report questionnaires lack the ability to capture decisions and states of the learners as they arise from circumstances in the learning environment and develop during the learning process (Richardson, 2004). Consequently, recent research calls for measurement of achievement goals not only by questionnaires but also by online measures to grasp moment-to-moment actions and thereby the state aspect of goal orientation at a fine-grained level. One way to track goal orientation online is through traces in online learning environments (e.g., Zhou & Winne, 2012).

In an attempt to investigate potential relationships between online and offline measures for goal orientation and their predictive power for learning outcomes, Zhou and Winne (2012) enriched an instructional text presented online with a set of hyperlinks and tags referring to the four different goal orientations (mastery-approach, mastery-avoidance, performance-approach, performance-avoidance). Hyperlinks to be selected were presented next to the text (e.g., "take a practice test on this"; performance-approach). Within the text students could use highlighting to structure the text and label highlights (e.g., "I want to learn more about this"; mastery-approach; Zhou & Winne, 2012, p.415). Selection of hyperlinks and tags were interpreted as online traces for the respective goal orientation. Zhou and Winne (2012) found that goal orientation as assessed by questionnaire data do not correlate with goal orientation as assessed by the traces captured online during the learning process. These findings are in line with earlier research indicating that self-reported measures of study tactics do hardly correspond to respective online measures collected during learning (Jamieson-Noel & Winne, 2003). The differences between online measures and questionnaire data for goal orientation could be partly seen as an indication of state-trait differences in goal orientation. Additionally, Zhou and Winne found an advantage of online traces over questionnaire data to predict learning outcomes, which raises the following question: Are online measures "better" than questionnaire data to assess goal orientation for educational purposes?

Another potential advantage of measuring goal orientation online is that it is less obtrusive compared to explicitly asking questions upon which students have to reflect. For example, intelligent tutoring systems could use tracking data that are collected during the learning process to estimate students' goal orientation at any given point in the learning phase and adapt their responses to the students' motivation and attitudes (e.g., Arroyo, Cooper, Burleson, & Woolf, 2010). Such adaptation could make intelligent tutoring systems even more effective (for an overview of recent advances in intelligent tutoring systems, see Graesser, Conley, & Olney, 2012).

Cognitive Tutors and other intelligent tutoring systems have proven to be very effective in supporting individual students' learning in a variety of domains such as mathematics or genetics (for an overview, see Koedinger & Corbett, 2006) and are widely used in schools across the United States as part of the regular mathematics curriculum. Based on an online assessment of students' learning, Cognitive Tutors provide individualized support for guided learning by doing. Specifically, the Tutor selects appropriate problems, gives just-in-time feedback, and provides hints. Additionally, students can use a glossary to look up definitions and explanations. Hints provide direct instructions for the next step a student has to determine; they are context sensitive and therefore adaptive to the situation. The glossary offers definitions and explanations for principles to be understood and learned; it is context insensitive and therefore not adaptive to the specific situation (Koedinger & Aleven, 2007). In light of achievement goal theory one could interpret the use of hints as performance-goal oriented and the use of a glossary as mastery-goal oriented behavior. Although hints can be used in a mastery-goal oriented way, specifically if students reflect upon them, they are often not used in this way. Their adaptive nature to the problem at hand suggests their use in order to immediately solve a problem rather than to deeply reflect and understand the underlying principle. Sometimes students even abuse hints in order to proceed quickly through the learning environment, a behavior referred to as "gaming-the-system" (Baker, Corbett, Koedinger, & Wagner, 2004). The glossary, in contrast, is not directly related to a to-be-determined problem step at hand. Therefore, we assume that it is consulted whenever students are interested in information that goes beyond the immediate problem-solving step. We claim that this behavior may be related to mastery-goal orientation as, in contrast to hint use, it does not primarily improve immediate performance in the learning environment but understanding. Using online tracking data of hint and glossary use could therefore be an unobtrusive and more proximal, "state-like" indication of goal orientation compared to the more reflected and "trait-like" measures gained by questionnaires. In addition, the data are tracked automatically, not taking up additional resources on either the side of the program or the learner.

The Present Study

Attempting to test if the findings of Zhou and Winne (2012) can be conceptually replicated in a different learning environment, and if hint and glossary use could be valid behavioral indicators for goal orientation, we reanalyzed a data set from an earlier study where students learned geometry principles using the Cognitive Tutor Geometry® (Salden, Aleven, Renkl, & Schwonke, 2009). First, we tested if self-reported goal orientations as assessed by a questionnaire correspond to the respective online measures.

Second, we assumed, as in the study by Zhou and Winne (2012), a positive relationship of glossary use and learning outcomes (i.e., understanding) and a negative relationship of hint use and learning outcomes. In our study, the learning outcome tests (i.e., posttests) - presented immediately after the learning phase and one week later - measured not so much knowledge of routines but application and understanding of the principles learned in the Cognitive Tutor. Our expectations were also in line with earlier studies showing better learning outcomes for mastery-oriented students than for performance-oriented students (for an overview, see Urdan, 1997). In addition, other studies on the Cognitive Tutor found negative relations between hint use and learning outcomes (e.g., Aleven &

Koedinger, 2001).

Third, while Zhou and Winne (2012) did not find a significant relationship of questionnaire data with performance on posttest, theoretical considerations as well as earlier studies led to the expectation that such a relationship may exist (for an overview, see Urdan, 1997). We therefore addressed the ("two-sided") research question (as did Zhou and Winne) if online and questionnaire data alike relate to learning outcomes.

Fourth, we checked if behavioral indicators for mastery as well as performance goal orientation (i.e., glossary and hint use, respectively) are stronger predictors of learning outcomes than respective questionnaire data.

To even out potential influences of prior knowledge on posttest performance we controlled for math grade (the strongest predictor of learning outcomes in this study) in all calculations involving posttest performance. More specifically, we addressed the following research questions:

(RQ1) Do self-reported goal orientations from the questionnaire correlate with respective behavioral indicators (i.e., hint use with performance goal orientation and glossary use with mastery goal orientation)?

(RQ2) Is there a positive relationship between glossary use and learning outcomes and a negative relationship between hint use and learning outcomes?

(RQ3) What is the relationship between questionnaire data of goal orientation and learning outcomes?

(RQ4) Are behavioral indicators for goal orientation better predictors of learning outcomes than the respective questionnaire data (i.e., are glossary and hint use better predictors for learning outcomes than self-report measures)?

Method

Sample and Design

Participants in our study were 57 students (19 in 9^{th} grade and 38 in 10^{th} grade; age: M = 15.63, SD = .84) from a German “Realschule”, which is equivalent to an American high school. The original study comprised three conditions to which participants were randomly assigned resulting in an equal distribution of 19 students per condition. In two conditions students were provided with worked examples to solve the mathematical problems. Worked examples were either faded out according to a fixed procedure (*fixed fading condition*) or according to the student’s individual skill level (*adaptive fading condition*). The third condition served as a control and did not receive any worked examples (*problem condition;* Salden et al., 2009). For the purpose of the reanalysis of our data for this paper, that is to investigate potential relationships between online and questionnaire measures of goal orientation and learning outcome, we examined all 57 participants as one group. To preclude potential influences of conditions on the observed relationships, however, we routinely calculated all analyses for the separate conditions and checked for potential significant differences. However, no such differences were found.

Learning Environment – The Cognitive Tutor

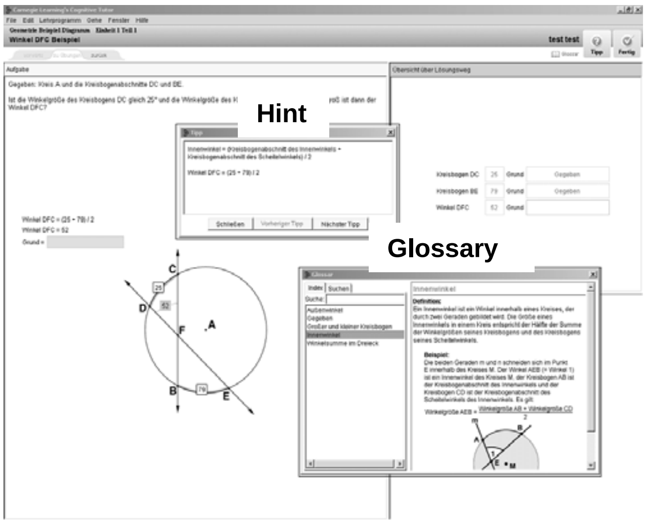

Figure 1. Screenshot of the Cognitive Tutor Geometry®

Cognitive Tutors provide adaptive feedback and model students´ skill acquisition based on two algorithms: *model tracing* and *knowledge tracing* (Koedinger & Corbett, 2006). Simulating the problem solving process enables the Tutor, for example, to provide specific hints for a problem situation. Also, all steps (i.e., all actions a student takes while working with the program) are tracked in a logfile. This data are used online for adaptation. For the purpose of this paper we analyzed part of this logfile data, specifically the amount of hint and glossary use (percentage in relation to all activities of the student in the learning environment), and correlated them with offline data of a goal orientation questionnaire and posttest scores.

Learning Materials During the learning phase with the Cognitive Tutor we asked students to work on fifteen problems in a Cognitive Tutor lesson on geometry, covering four geometry principles. The first eight problems required the application of only one geometry principle. The last seven problems combined different principles and were therefore more complex. Before the learning phase we provided students with instructions about the different tools in the Tutor. More specifically, after giving an overview of the learning environment, hints were introduced as an assistance tool to use when “having trouble solving a task or when reaching an impasse. The glossary was introduced as an assistance tool to use if “you are unsure when to use a certain mathematical principle or which is the corresponding formula”. These instructions were routinely used in several of our studies involving the Cognitive Tutor Geometry (e.g., Salden et al., 2009; Schwonke et al., 2012).

Instruments

Pretest The pretest was integrated in the Cognitive Tutor and consisted of four geometry problems related to the lessons taught later during the learning phase with the program. All Cognitive Tutor help facilities (e.g., hints) were disabled during the pretest. On average students needed 21 minutes to complete the pretest. Mathematics grade was a significantly stronger predictor of posttest performance than the pretest. Therefore, we included mathematics grade and not pretest scores in all analyses referring to posttest performance.

Goal Orientation Questionnaire Before solving the posttest, students were asked to answer 8 items concerning their learning goal orientation while working with the program on a scale from 1 to 6. Items were adapted from Elliot and McGregor (2001) and reflected mastery-approach and performance-approach goal orientations only.

Posttest A posttest consisting of the same problems as the pretest was implemented in the learning environment. Additionally, all participants were asked to complete a paper-pencil test immediately after working with the Tutor and one week later (delayed posttest). Immediate and delayed posttests were identical. On average students needed 31 minutes to complete the posttest and 21 minutes to complete the delayed posttest.

Procedure

The first experimental session lasted 90 minutes on average and was divided into three parts: pretest and introduction, learning phase in the Cognitive Tutor, and questionnaire on goal orientation as well as posttest. First, students´ general prior knowledge was assessed by their mathematics grade together with additional demographic data such as age and gender. Then they received a brief introduction on how to use the Cognitive Tutor followed by a short pretest implemented in the Tutor measuring their prior knowledge. After completing this pretest, students read an instructional text providing information about the rules and principles that were later addressed in the Cognitive Tutor. In the tutoring part, students worked with their respective version of the Cognitive Tutor. This learning phase was followed by a questionnaire measuring goal orientation with self-report measures and a knowledge test. The students worked again on the knowledge test in a second session (one week later).

Results and Discussion

To test if questionnaire data for goal orientation align with respective online measures (RQ1) we determined Pearson's correlations between assumed behavioral indicators for goal orientation (i.e., glossary use for mastery goal orientation and hint use for performance goal orientation) and self-report questionnaire data. There was no significant relationship between glossary use and mastery goal orientation (r = .13, p = .339) or hint use and performance goal orientation (r = -.14, p = .298). These findings are in line with Zhou and Winne (2012). The missing relationship between behavioral data collected online and questionnaire data collected after the learning phase may indicate that the two measures capture different constructs. One theoretically plausible interpretation is, that both the online measures collected by Zhou and Winne and our behavioral data, that is, hint and glossary use may reflect state goal orientation while questionnaire data may capture the trait aspect of goal orientation. However, one could argue that state and trait measures of other psychological constructs are generally correlated which raises the question of construct validity of the online measures. Therefore, more data is needed to decide if online measures and specifically behavioral data as the ones used in our study can be validly used as indicators for (state) goal orientation, if they differ systematically from the assumed trait measures of questionnaire data, and how both state and trait mutually affect each other. However, our data provides some initial evidence for the validity of hint and glossary use as measures for goal orientation:

First, we determined the correlation between glossary and hint use and found a very strong negative correlation: r = -.84, p < .001. This indicates that students had a relatively clear preference for either hints or glossary which is in line with the assumption that the type of tool use indicates whether the students were primarily concerned about solving the problems (i.e., performance orientation) or understanding the principles (i.e., mastery orientation) while working on the Cognitive Tutor lessons.

Second, we tested if glossary use is positively related and hint use is negatively related to learning outcomes (RQ2) which should be the case if these online measures can be associated with goal orientation. We determined partial correlations between glossary and hint use and the immediate and delayed posttest performance, controlling for prior knowledge. Results indicate a significant positive relationship for glossary use and immediate (r = .37, p = .008) posttest score. Correlation of glossary use and the delayed posttest score slightly failed to reach statistical significance (r = .28, p = .050). There was a significant negative relationship between hint use and performance on the immediate (r = -.48, p < .001) as well as the delayed (r = -.36, p = .009) posttest score. These relations can be seen as evidence that glossary and hint use may indeed be valid indicators for goal orientation. This may specifically be true as our posttests measured deep understanding of the principles learned in the Cognitive Tutor and not so much knowledge of routines. In a test measuring the later, differences between primarily performance versus mastery goal oriented students may not be as pronounced. Additionally, interpreting hint use as a measure for performance goal orientation may provide one explanation for the repeatedly found negative relations between hint use in the Cognitive Tutor and performance on posttest.

We further tested the relationship between self-reported mastery and performance goal orientation (i.e., questionnaire data) and learning outcomes (RQ3). We found a significant positive relation between mastery goal orientation and delayed posttest scores (*r* = .41, p = .003). The relationship between mastery goal orientation and immediate posttest scores (*r* = .25, p = .076) slightly failed to reach statistical significance. There was also no significant relationship between self-reported performance goal orientation and immediate posttest scores (*r* = -.21, p = .144); the relationship between performance goal orientation and delayed posttest scores (*r* = -.24, p = .086) failed to reach statistical significance. These results are, at least partly, in contrast to Zhou and Winne (2012) who observed no statistically significant correlations between self-reported goal orientations and posttest performance. However, the results are in line with theoretical assumptions and earlier studies using questionnaire data on goal orientation and further corroborate the aforementioned relation between goal orientation and learning outcomes.

To test if online measures or their respective questionnaire data are better predictors for learning outcomes (RQ4) we calculated separate stepwise linear regression analyses, one for mastery goal orientation (glossary use and respective questionnaire data) and one for performance goal orientation (hint use and respective questionnaire data) as potential predictors for immediate and delayed posttest performance. Concerning the predictive power of mastery goal orientation (glossary use vs. questionnaire data) for posttest scores results are mixed: While glossary use was the sole best predictor for immediate posttest scores, questionnaire data was the best predictor for delayed posttest scores (Table 1). With regard to the predictive power of performance goal orientation (hint use vs. questionnaire data) for posttest scores, there was a clear advantage of the behavioral data: Hint use was the sole best predictor for both immediate and delayed posttest scores (Table 2). Taken together, our results indicate that specifically for mastery goal orientation questionnaire data might yield predictive power beyond behavioral online data, at least for long-term learning effects. These results are not fully in line with Zhou and Winne (2012) who consistently found online measures to be the stronger predictors of learning outcomes in regression models. There might be methodological explanations for the differences between the two studies: We used a different questionnaire as basis for our goal orientation items and measured only two and not four aspects of goal orientation. Also, the questionnaire used by Zhou and Winne did not relate significantly to learning outcome measures. In addition, utilizing hint and glossary use as indicators for goal orientation might be a little more "indirect" as compared to the online data collected by Zhou and Winne (2012). For example, hint use might also be elicited by errors made when trying to determine solution steps, that is, it may be related to rather poor performance in the learning environment. However, the very strong negative correlation of *r* = -.84 between hint and glossary use cannot be explained by these errors (partial correlation controlling for errors is still highly significant with *r* = -.73, *p* < .001).

Table 1: Glossary Use and Mastery Goal Orientation as Predictors for Learning Outcomes

		B	*SE B*	*β*
Posttest	Step 1			
	Glossary Use	.22	.06	.42**
Delayed Posttest	Step 1			
	Items on Mastery Goal Orientation	.09	.03	.38**
	Step 2			
	Items on Mastery Goal Orientation	.08	.03	.35**
	Glossary Use	.16	.06	.30*

Note. Posttest: R^2 = .18 for Step 1; Delayed Posttest: R^2 = .15, ΔR^2 = .09 for Step 2 (*p* < .05).
* p < .05 and ** p < .01.

Table 2: Hint Use and Performance Goal Orientation as Predictors for Learning Outcomes

		B	*SE B*	*β*
Posttest	Step 1			
	Hint Use	-.71	.15	-.53***
Delayed Posttest	Step 1			
	Hint Use	-.56	.17	-.42**

Note. Posttest: R^2 = .28 for Step 1; Delayed Posttest: R^2 = .18.
** p < .01 and *** p < .001.

Taken together, both behavioral online and offline questionnaire data provide us with important insights for understanding learners´ goal orientation and can be used to supplement rather than to replace each other for the sake of scientific advancement. Given the high predictive value of behavioral online data, however, their use should be considered for educational purposes in classrooms and specifically in online learning environments, where an unobtrusive and efficient collection of goal orientation data could improve adaptation in intelligent tutoring systems and thereby foster the learning process. In addition, one should keep in mind that self-report measures of characteristics such as goal orientation are potentially subject to a social desirability bias which could be circumvented with (indirect) online measures.

Can help seeking behavior in intelligent tutoring systems be used as online measure for goal orientation? Even though we cannot answer this question based on our data conclusively, our results provide a first and promising indication that online behavior in intelligent tutoring systems provides an unobtrusive and efficient additional or even alternative measure to questionnaire data to assess goal orientation in educational settings.

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