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Investigating How Achievement Goals Influence Student Behavior in Computer Based Learning

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Abstract: This study uses a mixed methods approach to explore relationships between goal achievement orientation and changes in student achievement, behavior, and affect while using Betty's Brain. Qualitative coding was applied to student interviews to identify either performance or mastery goal approaches applied during their interaction with the game. A combination of quantitative methods were used to determine the influence and strength of goal orientations on student outcomes and interviews were thematically examined for patterns across student experiences. Findings from this study imply that students who communicate a goal approach (either performance approach or mastery approach) are more likely to experience confusion and engage in review-related behaviors such as reading informational resources and noting the accuracy of their responses.

Keywords: Education, achievement goals, human-computer interaction, affect and behavior

1. Introduction

Achievement Goal Theory seeks to understand how differences in students' goals influence their learning behaviors (Elliot & McGregor, 2001). Elliott & Dweck, (1988) identified two primary goals in achievement situations: performance goals (which involve attempts to maintain positive perception of one's own abilities) and mastery goals (which involve the pursuit of new knowledge or skill mastery mastering a new task). They also sought to classify these goals in terms of valance, a classification that proved useful in a wide range of research (Pintrich, 2000; Senko, Hulleman, & Harackiewicz, 2011). Negatively-valanced orientations (i.e., avoidance goals) have been shown to negatively impact achievement, educational interest, study habits, help-seeking, and increase anxiety (Senko et al., 2011; Wolters, 2004). However, positively-valanced goal orientations (i.e., approach goals) are associated with positive outcomes, including reduced anxiety, increased effort and persistence, increased performance, and help-seeking behavior (Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Niepel, Brunner, & Preckel, 2014; Wolters, 2004).

In general, mastery goals may seem preferable to performance goals. Considerable research shows that mastery approach goals have the potential to improve cognitive, motivational, and behavioral processes, including improvements related to anxiety and help-seeking behavior (Wolters, 2004). However, recent findings suggest that mastery avoidance goals are extremely rare in real-world learning (Skaalvik, 2018) and performance-approach goals have also been associated with positive outcomes (such as increased effort, persistence, and performance; Harackiewicz et al., 2002; Niepel et al., 2014). In fact, the behavior and dynamics around these goals are often moderated by contextual factors such as motivation, reception of feedback, autonomy, interest, and self-regulated learning (Wilson & Narayan, 2016). The complexity of the patterns around achievement goals suggest that it may be valuable to investigate their emergence in greater detail.

This study uses a mixed-methods approach to examine goal achievement in interviews conducted with students as they interact with a computer-based science learning environment. Specifically, we use data from Betty's Brain, where a range of both positive and negative affective states have already been studied (Andres et al., 2022; Hutt et al., 2021). In past studies of these interviews, we examined the relationship between affect and anxiety as well as the differences in student perceptions in response to frustration (Andres et al., 2022; Baker et al., 2021). In this article, we examine how students' achievement goals interact with students' affect, metacognitive and problem-solving strategies, and learning outcomes. We leverage a combination of open-ended interviews, log data, and affect detectors to analyze how achievement goals may be impacting student experiences in this system.

2. Methods

2.1. Betty's Brain

Betty's Brain is an open-ended, computer-based learning system that implements a learning-by-teaching model. Students teach a virtual agent named "Betty" by creating a causal map of scientific processes (e.g., thermoregulation or climate change; Leelawong & Biswas, 2008). Students choose how to navigate a variety of learning resources as they build their maps and quiz Betty. These quizzes are used to demonstrate Betty's "learning" and are graded by a mentor agent, Mr. Davis, who scaffolds students' learning and teaching endeavors (Biswas, Segedy, & Bunchongchit, 2016).

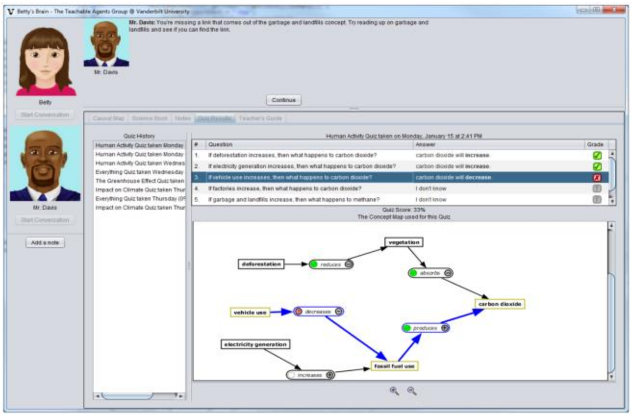

Fig.1. *Screenshot of quiz results and the causal map Betty uses to answer quiz questions*

2.2. Study Design

Data was collected at an urban middle school in the Eastern United States, from 99 sixth-graders (approximately 11-12 years old) who used Betty's Brain in their regular science classes. Their school's population is approximately 60% White, 25% Black, 10% Asian, and 5% Hispanic, with approximately 10% enrolled in the free/reduced lunch program. Individual demographics were not collected. The same students used Betty's Brain to complete two science inquiry scenarios conducted in December 2018 (study 1) and February 2019 (study 2). Data were collected over the course of seven school days in both time periods. Students and their parents were consented/assented prior to the study. On the first day of the study, students completed a 30-45-minute paper-based pre-test. On day 2, students participated in a 30-minute training session that familiarized them with the learning goals and user interface of the software. Following the pre-test and training, students used the Betty's Brain software on days 2 through 6, for approximately 45-50 minutes each session, using concept maps to teach Betty about the causal relationships about science content. On day 7, students completed a post-test that was identical to the pre-test, in order to assess their learning.

Students used Betty's Brain to complete a causal map about climate change (study 1) or thermoregulation (study 2). During both studies, interviews explored how students were working with the system during specific experiences. As students interacted with Betty's Brain, automatic detectors of educationally relevant affective states (Jiang et al., 2018) and behavioral sequences (Munshi et al., 2018), embedded in the software, identified specific affective patterns or theoretically aligned behavioral sequences. Jiang et al.'s, (2018) real-time affect detection—which had been previously integrated into Betty's Brain included BROMP-based detectors (Ocumpaugh, Baker, & Rodrigo, 2015) of boredom, confusion, engaged concentration, delight, and frustration. Each detector generated an affect prediction (a probability between 0 and 1) every 20 seconds based upon the student's interactions.

These detectors were used to select which student to interview at a specific time, with a focus on shifts in affect or meaningful behavioral patterns indicating self-regulated learning (Hutt et al., 2021).

At the end of study 2, science anxiety surveys were administered alongside questions about students' perceptions of difficulty and familiarity with the topic and questions about Mr. Davis. Between the two studies, minor changes were made to Betty's Brain, including small changes to make Mr. Davis seem more polite (Ocumpaugh et al., 2021). All other procedures were identical.

2.3. Student Interviews and Interview Coding

A total of 594 interviews (358 in study 1; 236 in study 2) were obtained. Interviewers sought a helpful but non-authoritative approach when speaking with students, often asking students what their strategies were (if any) for getting through the system. Questions were added to elicit more information as new patterns and information emerged. Overall, students were encouraged to speak about what they wanted and their feedback about their experience with the software. Audio files from the interviews were collated and stored on a secure file management system available only to the research team members. Three members of the research team manually transcribed the interviews in an agreed-upon format. Metadata, including timestamps and recording IDs, were preserved, but data was de-identified (i.e., each student was assigned a unique alphanumeric identifier).

The code development process followed the recursive, iterative process used in previous research (Weston et al., 2001) that includes seven stages: conceptualization of codes, generation of codes, refinement of the first coding system, generation of the first codebook, continued revision and feedback, coding implementation, and continued revision of the codes (Weston et al., 2001). The conceptualization of codes included a review of related literature to capture meaningful experiences relevant to the study's research questions. Using grounded theory (Charmaz, 1983), a method that is appropriate for the kind of open-ended interviews where students are being asked to interpret their own experiences, we worked with the lead interviewer (the third author) to identify categories that were (1) relevant to either affective theory (e.g., D'Mello & Graesser, 2012) or self-regulated learning theory (e.g., Winne & Hadwin, 1998) and (2) likely to saliently emerge in the interviews.

A coding manual was created through the iterative refinement of this coding scheme, and multiple coders achieved an acceptable interrater reliability (Cohen's Kappa > .6) before coding the transcripts. The coders met and clarified any concerns to avoid misinterpretation or miscoding of the data. Although a number of coding schemes were developed in this manner (Baker et al., 2021), the current study focuses on codes that align with Achievement Goal Theory: performance approach or mastery approach. (Note that while the coding manual included performance avoidance, this code was rarely applied and was excluded from analysis.) As these qualitative codes are not mutually exclusive, a single interview may be coded under both categories. However, as Table 2 shows, this kind of overlap was infrequent.

Table 2. *Summary of coded interviews and unique participants associated with the interviews*

	Study 1 - December				Study 2 - February			
	Perf	Mas	Both	Neither	Perf	Mas	Both	Neither
Interviews	38 (11.76%)	59 (18.27%)	6 (1.86%)	232 (71.83%)	46 (19.49%)	46 (19.49%)	10 (4.24%)	154 (65.25%)
Students	31	42	6	29	33	33	8	38

2.4. Student Interaction Data: Affect and Behavior

In addition to pre-tests, post-tests, and interview data, we also extracted two different types of data from the logs of student interactions with the system. Affect predictions (generated every 20 seconds) were averaged to produce an rate of incidence for each affective state per student which was then used in the quantitative analyses of this study. The second were 26 SRL-related behaviors that could be distilled from the logs. Some behaviors include viewing explanations for questions, taking quizzes, and marking added responses as correct or incorrect.

2.5 Analysis

The analyses conducted in this study consider differences in student achievement (pre-test and post-test scores and gains), behaviors, and affect in response to the presence and kind of achievement goal approach students communicated. Rates of performance approach and mastery approach were generated for each student by dividing the total number of times each student's interview was coded for mastery approach or performance approach by the total number of times that student had been interviewed (as this varied by student). This calculation, though sufficient for the current analysis, is still limited by the number of interviews a student engages in and may result in lower achievement goal rates overall despite any explicit expression of an achievement orientation or goal within an interview.

We examine the differences between students who communicated a goal approach (combining the performance and mastery approach codes) to students who did not report a goal approach using t-tests and Linear Mixed Effects Models (LMEMs). Benjamini & Hochberg, (1995) post-hoc corrections were applied when a set of multiple tests was run. We also analyzed the interview data qualitatively, taking the interviews of students with at least one instance of a goal approach code, either performance or mastery, and examining these for recurring themes or responses. Pseudonyms were assigned to participants using *http://random-name-generator.info/* without reference to actual student gender.

3. Results

Our quantitative analysis first uses t-tests to explore the differences between those students who expressed either goal orientation to those who had not. In study 1, students with a goal orientation viewed informational resources more often than peers without a goal approach (M=.18, SD=.18, t(90)=-2.087, p=.04), but that effect flipped in study 2, where they viewed these same resources less often than their peers (M=.12, SD=.14, t(74)=1.998, p=.05). In Study 1, students with a goal orientation also exhibited more frustration than their peers (M=.73, SD=.09, t(90)=-2.136, p=.04). However, given the substantial number of behaviors, affective states, and achievement metrics (pre-test scores and learning gains) tested, these findings do not remain statistically significant after post-hoc correction and must be treated as suggestive but inconclusive.

LMEMs were fit to regress the interaction of pre-test scores and goal approach onto each student's total affective state (boredom, frustration, confusion, delight, engaged concentration). In each of these models (5 affective states observed in 2 studies), pre-test scores and goal approach rates were treated as fixed effects and student IDs as random effects. This approach was chosen due to the repeated (multiple sessions per student) and nested structure (sessions nested within students) of the data (Pinheiro & Bates, 2006). Results show that individual rates of goal approach positively predicted confusion in study 2 (β=.16, R^2=.057, p=.035), but did not significantly predict other states (p's = 0.11 to 0.97).

Additional t-tests were conducted to examine the differences among the 27 students who articulated either goal approach, comparing students who had above average rates against those with below average rates (above zero) of either goal approach orientation in their interviews. The results of this analysis indicate that students with below average goal orientation ratios were more likely to mark their causal links as correct in their maps (M=.008, SD=.12, t(27)=3.11, p=.005) and spent more time viewing graded explanations (M=1969.57, SD=2396.70, t(27)=2.21, p=.005). That is, they were more inclined to spend time reading explanations and verifying the accuracy of their responses, but they were also less likely to view explanations for ungraded questions than those with higher ratios (M=.004, SD =.01, t(27)=2.00, p=.05). However, as with the first set of T-tests, these trends do not remain statistically significant after post-hoc correction and must be treated as suggestive though inconclusive.

Our qualitative analyses suggest that students who had articulated a goal approach also discussed using Betty's Brain resources to evaluate the accuracy of their causal maps. Among students who expressed performance goals, Isabel said "I'm trying to figure out which ones are marked correct by asking Betty questions to figure out which ones are correct and which ones I need to mark wrong." This was remarkably similar to the statements by two students who expressed mastery goals during their interviews. For example, Tiffany reports "I'm just trying to go back to the textbook and find out what's happening right there so I can mark things, more things as correct." Likewise, Janie elaborates further on this process: "I just finished reading the science stuff so I'm going to go back to there and give her more quizzes and questions. And then if you see like which ones she (Betty) got wrong. And if she got like some wrong….I read more about that on the map....and [I] mark[ed] what's correct on the map." That is, both students with performance goals and students with mastery goals discuss these strategies in terms of correctness, a terminology that mimics the platform's assessments. Interestingly, students who had neither goal were more likely to mark themselves correct – but perhaps not as likely to carefully think about their correctness.

Students who had expressed either goal approach in their interviews also referred regularly to their in-game achievement. Among students who expressed a performance approach, Rosemary expressed a conscious effort to improve her scores, explaining that her "best was a 50 [percent] on the cold detection quiz, and now today I have 100's on both and then now I'm working to improve the…the overall score." Likewise, Wendy described "I got like 7 out of 10 right." Students with mastery approaches gave similar information in their interviews. Terrence, who expressed both performance and mastery approach goals, told the interviewer "I was taking a lot of quizzes… I made a new high score… Yeah, so that's a big improvement." Meanwhile, Carl, who exclusively expressed a mastery approach, said, "I started at 0, and then I took [quizzes] just to see what was going on and then I tested and I got two 20's, and then yesterday I got a 38, so it's…a good improvement." These responses suggest that students who express a goal approach also convey progress on their scores that has at times been achieved through their use of the tools within the platform.

These interview responses clarify what is seen in the quantitative analyses, suggesting that students with a goal approach are more diligent in taking note of the accuracy of their responses and of viewing informational resources that would help them to do so. Though neither analysis is fully conclusive, both quantitative and qualitative methods suggest differences in behavior and interaction, such as increased review-like behavior and commitment to score improvement, within the Betty's Brain platform between the students that have communicated a goal approach and those who have not.

4. Conclusions

This study uses a mixed-methods approach to explore relationships between goal achievement orientation and changes in student achievement, behavior, and affect while using Betty's Brain. Qualitative interviews were coded for performance approach or mastery approach orientations and then used for thematic analysis into student experiences. A combination of quantitative methods were used to examine the influence of goal orientations on achievement, affect, and behavior.

While we did not find differences between performance and mastery goals, we did find that a trend where having either of these orientations influenced review-related behavior and experiences of confusion. We also found that the number of times a student's goal orientation emerged in their interviews suggested possible differences in behavior such that students with below average rates of a communicated goal approach were more likely to exhibit review-related behavior and confirm the accuracy of their responses. Similar patterns were also seen in the qualitative analysis where students who had expressed either kind of goal approach discussed using in-game resources to verify the accuracy of their responses and express improvement and progress around their in-game achievement.

A key limitation of this study is the amount of data. While the current data set was sufficient for detecting some changes in relation to goal achievement, it is unable to capture the full range and diversity of influences that relate to these orientations. Future work should seek to collect more interviews and target interviews to more specifically prompt students about achievement goal orientation. However, the fact that goal orientation emerged unprompted suggests that simply having a goal approach causes salient effects; additional data might be sufficient to demonstrate that a students' unprompted expression of these goals is an important indicator, and the degree to which they continue to return to goal-related themes is a measurement that could be useful to both researchers and educators.

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