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Stability and change in adolescents' task-specific achievement goals and implications for learning mathematics with intelligent tutors

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ABSTRACT

Individuals' achievement goals are known to influence learning behaviors and academic achievement. However, prior research also indicates that undergraduates' achievement goals for psychology coursework vary from assignment to assignment. The effect of stability of achievement goals on learning behaviors and outcomes has yet to be explored. This study examined how adolescents' achievement goals varied over mathematics units completed in an intelligent tutoring system, and whether strength or variability in achievement goals influenced behavior or achievement. At the group level, achievement goals correlated significantly from unit to unit; mean scores were not significantly different over time. However, individuals' goal scores changed reliably across units. No relationships were found between the strength of students' achievement goal scores and learning behaviors or performance. However, students with stable mastery approach goals achieved better grades than those with more variable mastery-approach goals. Students with stable performance-approach goals engaged in fewer help-seeking behaviors than those with variable performance approach goals.

1. Introduction

When individuals engage in a learning task, they do so with specific kinds of achievement goals in mind. Some may wish to increase their competence by learning as much as they can. Others may seek only to demonstrate their competence by outperforming peers, or by completing the task quickly or without errors. Another group may wish only to avoid performing worse than others. Learners who endorse these mastery approach, performance approach, and performance avoidance achievement goals tend to engage in distinct learning behaviors, and to obtain different learning outcomes (Ames, 1992; Dweck, 1999; Elliot, 2005; Elliot & MacGregor, 2001; Elliot, McGregor, & Gable, 1999; Linnenbrink-Garcia, Tyson, & Patall, 2008). Mastery approach goals are associated with greater self-regulation and strategy use, and deeper processing of material (Ford, Smith, Weissbein, Gully, & Salas, 1998; Somuncuoglu & Yildirim, 1999). Performance approach goals are associated with a mixture of deep and shallow processing (Wolters, 2004), and performance avoidance goals are associated with shallow processing and less organized study behavior (Elliot et al., 1999). With respect to achievement, both mastery approach and performance approach goals have been associated with higher achievement (Linnenbrink-Garcia et al., 2008), whereas performance avoidance goals typically correlate with poorer achievement (e.g., Elliot & Church, 1997).

A considerable amount of research has examined how one's level of endorsement of achievement goals on a Likert scale (i.e., goal *strength*) relates to learning. However, little focus has been placed on the consistency of learners' endorsement of an achievement goal (i.e., goal *stability*). Most studies assess achievement goals only once during learning and thus implicitly assume that these goals are stable constructs that do not change between initial measurement and subsequent learning or performance. When achievement goals are measured only once, researchers are unable to capture variations in learners' endorsement of achievement goals over time. Though the vast majority of studies examining achievement goals do so with a single observation, a handful of recent studies have examined achievement goals repeatedly over a semester and demonstrate that individuals' goals can change over time and vary with respect to tasks (Fryer & Elliot, 2007; Muis & Edwards, 2009). These initial studies raise important questions regarding the stability of achievement goals, but had limited ability to examine how goal stability related to learners' behaviors.

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In this study, we pair frequent sampling of achievement goals with continuous observation of learning behavior to examine how the stability of learners' achievement goals relates to their leaning processes and achievement. We propose that (1) a fine-grained examination of achievement goals and behavior could provide further evidence that achievement goals fluctuate when measured in the context of learning tasks and (2) that the degree to which learners' goals are stable versus variable may have implications for learners' behaviors and outcomes.

We base this second assumption upon research in social psychology that demonstrates that personality variables often described as dispositional in the literature are also influenced by environmental factors. Mischel (1968, 1969) initially introduced the idea that personality should be thought of as contextual, and documented that individual's self-reports of anxiety and other personality variables tended to only correlate around $r = .3$ across measurements taken in different contexts. Many perceived that these findings called into question the utility of these variables as predictors of behavior, but Bem (1972; Bem & Allen, 1974) argued that one's tendency to maintain a consistent level of a personality characteristic across situations may itself be a useful individual difference variable that predicts future behavior. In a subsequent meta-analysis, Kraus (1995) examined the effect of attitudes on future behaviors documented in 88 studies and confirmed that the stability of one's attitudes moderates the relationship between attitude and behavior. Greater stability in an attitude increased its tendency to predict behavior.

In this study, we examined whether these findings regarding stability can be applied to the relationship between achievement goals and learning. We examined the relationship between the strength (i.e., self-reported endorsement of an achievement goal) and stability (i.e., consistency of endorsement across multiple learning tasks) of achievement goals and adolescents' learning behaviors and performance in a high school math course. We assessed students' achievement goals for math tasks by embedding achievement goal measures into units of an intelligent tutoring system for geometry (Aleven & Koedinger, 2002; Koedinger & Aleven, 2007) and observed their learning behaviors in these units and performance in the course. We then analyzed whether individuals who maintained a stable level of achievement goal endorsement behaved or performed differently from those whose achievement goals varied across tutoring units.

1.1. Theoretical basis for stability and change in achievement goals

Achievement goals both originate from individuals' personal characteristics and are influenced by features of learning environments. Achievement Goal Theory suggests that individuals' achievement goal orientations are stable to the extent that they derive from individuals' achievement motives (Elliot & Church, 1997; Harackiewicz, Barron, & Elliot, 1998) and temperament (Elliot & Thrash, 2002). Because these characteristics are theorized to be dispositional, one might expect some stability in achievement goals over time and across tasks (Elliot & Thrash, 2001).

There are also reasons to expect that achievement goals should vary. Learners' achievement goals can be influenced directly by personal characteristics that are themselves variable. For example, within a single science course, a student may be interested in one topic, like genetic mutation, but disinterested in another, like genetic inheritance. Because individual interests have been found to predict mastery goal adoption (Harackiewicz, Durik, Barron, Linnenbrink-Garcia, & Tauer, 2008), a learner would be expected to pursue mastery goals when studying materials describing mutation, but less so when given materials describing inheritance. Achievement goals should also vary when an individual is given multiple learning tasks that impose different goal structures. For instance, mastery goal adoption can be induced by giving individuals directions that tell them they are supposed to learn, whereas performance goal adoption can be induced by telling individuals that their performance on the task will be evaluated to assess their competency (e.g., Darnon, Butera, & Harackiewicz, 2007). To the degree that a series of learning tasks vary in interest to learners or are structured to suggest different implicit goals, learners' achievement goals should vary.

The degree to which individuals are consistent in their goals should also have an impact on their learning processes and outcomes. For instance, a student who is consistently focused on deeply understanding concepts (i.e., consistently pursues a mastery approach goal) should show evidence of deep learning and achieve positive outcomes as a result. A learner who is consistently focused on outperforming peers (i.e., consistently pursues a performance approach goal) should demonstrate behaviors that are likely to deliver strong performances in tasks. In this study, we examine the stability of students' achievement goals for mathematics units by observing their achievement goals in each unit. We then examine how a stable versus variable achievement goal relates to students' learning behaviors by examining their behaviors in units and their performance in their math course.

1.2. Prior research on stability and change in achievement goals

Five studies have found evidence of both stability and change in achievement goals (Fryer & Elliot, 2007; Muis & Edwards, 2009). Fryer and Elliot (2007) conducted three studies examining undergraduates' achievement goals for exams in a psychology course. These studies assessed students' achievement goals three or four times over a semester and found that students' mastery-approach, performance-approach, and performance-avoidance goals for exams correlated significantly within each goal across observations. Analyses using mean scores also indicated that achievement goals were generally stable over time. For example, dependent *t*-tests examining mean scores per goal between time points revealed that from Time 1 to Time 2, mastery approach goals decreased and performance avoidance goals increased, but were more stable from Time 2 to Time 3 (Studies 1, 2, & 3; Fryer & Elliot, 2007). Performance approach goals were found to be stable across observations. These analyses using mean scores as criteria indicated that after some early adjustment, learners' achievement goals were generally stable. However, when analyses of individual-level change were conducted, evidence of variability in individuals' goals emerged. Using a Reliable Change Indices (RCI; Christensen & Mendoza, 1986; Jacobson & Truax, 1991) that examines differences across pairs of observations, researchers have determined that an individual's achievement goals tend to vary. Across five studies examining achievement goals in conjunction with writing assignments and exams, more than three in four learners reported reliable change in their achievement goals from one observation to another (Fryer & Elliot, 2007; Muis & Edwards, 2009).

Muis and Edwards (2009) also examined the relations between learners' achievement goals for assignments (i.e., exam or writing assignment) and their performance on the assignments in their psychology course. In some cases, performance on the writing task was significantly and positively related to students' mastery goal scores for the task, and negatively to performance-avoidance scores. However, these associations were not consistent across repeated observations, leaving the relationship between task-specific achievement goals and performance unclear. Importantly, no prior study has examined how the stability of learners' goals influenced their performance in the course. That is, we do not know whether a students' tendency to change their goals from one task to the next will have an impact on performance in the course. Additionally, neither set of studies recorded students' learning behaviors. As a result, we know nothing about the relationship between achievement goal stability and learning behaviors.

1.3. The current study

The first goal of this study was to extend investigations of stability and change in achievement goals to a new population of students whose achievement goals were assessed via learning technology and in the context of a problem-solving task. We examined whether the patterns of stability and change observed in undergraduates would extend to high school populations using intelligent tutoring systems. We embedded questionnaires into the geometry units that students completed in the intelligent tutoring system (ITS or "tutor") they used in their math course. We then conducted the same mean-level and individual-level analyses conducted in earlier studies.

A second goal of this study was to determine whether the stability of learners' achievement goals would affect their behavior or performance. Unlike prior studies that assessed achievement goals using paper-based measures in a classroom context, we capitalized on the affordances of the ITS to examine students' achievement goals and learning behaviors via the learning technology. For each unit the students completed, they reported their achievement goals and the ITS recorded their actions in a log-file. We used these log-files to identify specific learning behaviors (e.g., the number of times a learner requested a hint in the unit), and tested whether those with stable versus variable achievement goal scores would differ in their behavior or performance. We posed the following research questions:

1. How stable are high school geometry students' achievement goals for learning math with an intelligent tutoring system?
2. How does the strength of students' achievement goals relate to their behavior in an ITS setting and their performance in a course?
3. Do those whose achievement goals are highly stable across units behave or perform differently than those whose goals vary?

2. Methods

2.1. Participants

Sixty-seven students who used an intelligent tutoring system as part of their math course participated in a larger study of motivation. The sample was 47% female and was drawn from a rural high school in the Northeastern US in which 21% of students qualified for a free or reduced lunch. In the year the study was conducted, 95% of students enrolled at the school were classified as Caucasian (3% African-American, <1% Hispanic, Asian or other). Students were primarily juniors around 15–16 years old. Because they completed units at their own pace, students varied in the total number of units and the span of units they completed during the study. In order to answer our research questions, we examined data from a set of 28 students who completed a span of five units containing achievement goal measures.

2.2. Materials

Participants spent nine months (i.e. September through May) completing units in Cognitive Tutor Geometry, an intelligent tutoring system (Carnegie Learning, 2012). After three months (i.e. in January) the software was modified to present achievement goal measures in each unit. Course grades served as a measure of performance.

2.2.1. Cognitive Tutor Geometry

Cognitive Tutors are a family of intelligent tutoring systems that combine cognitive psychology and artificial intelligence to construct computational cognitive models of learners' knowledge as they learn mathematics (Koedinger & Aleven, 2007; Koedinger & Corbett, 2006). Cognitive Tutors support tutored problem solving by providing step-by-step guidance and individualized problem selection as students solve complex problems (Fig. 1). In particular, the tutor helps students to break problems into steps and provides correctness feedback and context-specific advice with respect to these steps. As students complete problems, their progress towards mastery of skills is monitored and displayed in a *student model* depicted in the interface as a skill meter. Students may also use a help feature that presents support that is customized to the problem step being attempted. These are available by clicking on a "hint" button in the interface. Hints are structured hierarchically and provide increasingly detailed assistance. The first hint typically restates the problem step, the intermediate hint(s) point out a problem-solving principle, formula, or relevant feature of the problem, and the final hint provides the answer to a step. The tutor logs all students' actions in the environment in order to monitor students' learning. In each unit, students are exposed to an introductory reading that is presented in conjunction with a set of targeted skills followed by problem sets that provide opportunities to practice skills that correspond to learning objectives.

For this study, we examine learning behaviors in a span of five units. These behaviors included the number of hints requested (help seeking), the number of problems needed to acquire mastery (i.e., efficiency), and the percent of problem steps completed correctly (i.e., accuracy). The tutoring software is designed to help students become efficient problem solvers who can accurately complete problem steps that require mastery of specific skills. We measured help seeking to assess students' willingness to use the step-specific guidance provided by the software and examined the number of problems needed to complete the unit in order to assess how efficiently their learning behaviors are in bringing about mastery of targeted skills. Accuracy served as a measure of students' relative ability to complete steps without making errors and can be thought of as a unit-specific measure of performance.

2.2.2. Achievement goals

We assessed students' achievement goals *microgenetically* (Bernacki, Nokes-Malach, & Aleven, 2013), by repeatedly assessing their goals for math units using a version of the Achievement Goals Questionnaire Revised (AGQ-R; Elliot & Murayama, 2008) that we adapted for the study. The original AGQ-R is a twelve-item scale that assesses each of four achievement goal orientations with a set of three Likert scaled items. Using the microgenetic method, two items from each subscale with the highest reported factor loadings reported by Elliot and Murayama (2008) formed the mastery approach, performance approach and performance avoidance subscales (e.g., mastery approach item: "In this unit, my goal is to learn as much as possible"). These *unit-specific* achievement goal questionnaires were embedded in each Cognitive Tutor unit and were completed for the duration of the spring semester. Likert items were scaled 1 (strongly disagree) to 6 (strongly agree). Cronbach's alphas for each scale on each of five administrations of the two-item task-specific scales demonstrated that measures were typically of adequate reliability (see Table 1).

2.2.3. Course grades

Students received a course grade from their instructor based on their performance on classroom assignments and exams (scored 0–100 and not including tutor performance). The mean grade for the third quarter was 79.07% ($SD = 6.54$), and the content covered in the quarter corresponded to content covered by Cognitive Tutor

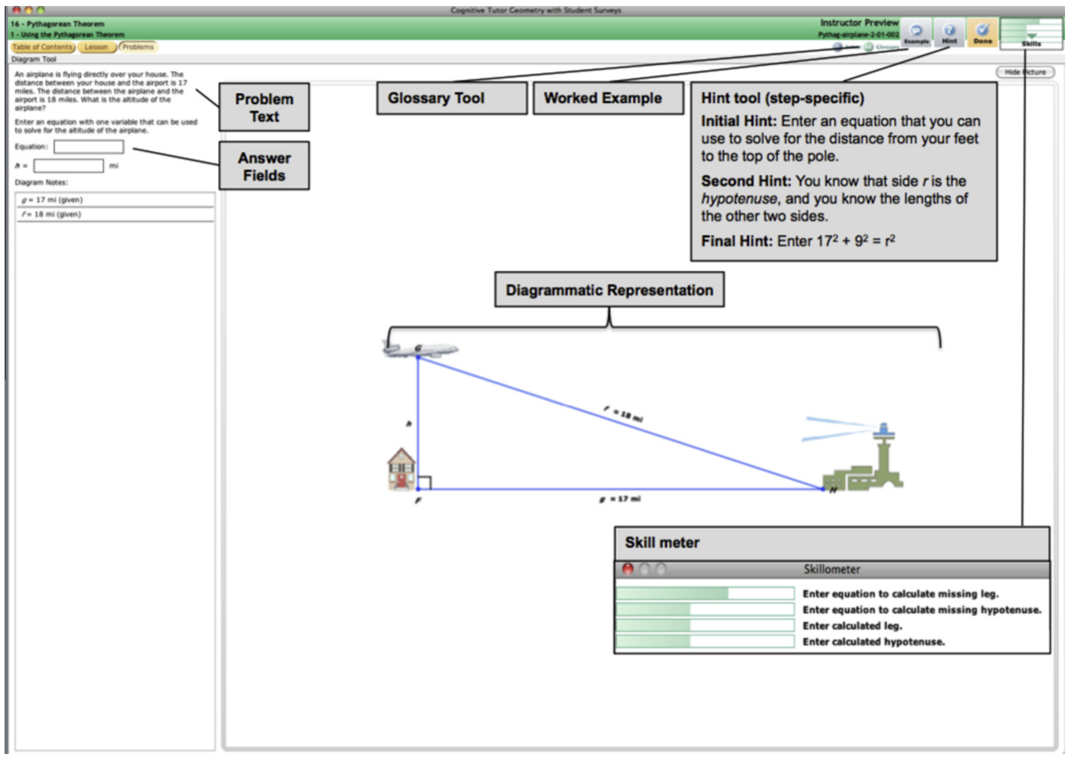

Fig. 1. Screen shot of a Cognitive Tutor Geometry problem in a unit on Pythagorean Theorem, depicting problem content and tutor features. The gray boxes are annotations added by the authors (i.e., not part of the tutor interface).

Table 1
Descriptive statistics for unit-specific achievement goal orientations per unit.

	Time 1 Unit 12 Perimeter and area of Trapezoids			Time 2 Unit 14 Perimeter and Area of a Composition			Time 3 Unit 16 Properties of Triangles			Time 4 Unit 18 Pythagorean Theorem			Time 5 Unit 20 Ratios and Proportions		
	M	SD	α	M	SD	α	M	SD	α	M	SD	α	M	SD	α
Achievement goals															
Mastery approach	4.05	1.28	.62	4.23	1.27	.93	4.04	1.04	.93	4.38	.97	.88	4.41	.99	.73
Performance approach	3.98	1.40	.69	4.14	1.45	.97	4.13	1.17	.91	4.16	1.05	.79	4.45	.95	.97
Performance avoidance	3.88	1.74	.85	4.32	1.47	.89	4.13	1.09	.62	4.27	1.06	.96	4.46	1.06	.70
Behaviors	M	SD	Min, Max	M	SD	Min, Max	M	SD	Min, Max	M	SD	Min, Max	M	SD	Min, Max
Efficiency	28.00	9.35	13.00 52.00	19.50	4.80	14.00 33.00	27.56	5.95		15.89	5.35		77.04	9.38	
Hint Requests	10.00	11.05	0.00 52.00	3.50	3.85	0.00 11.00	31.43	18.71		8.86	9.72		15.25	14.77	
Accuracy	95.66	2.91	89.57 100.0	96.66	1.67	92.31 99.12	88.52	3.95	78.49 94.76	85.12	8.56	69.07 100.0	90.76	3.57	80.54 98.73

units including those under observation in this study. It did not include any measure of student completion of or performance in Cognitive Tutor units.

2.3. Procedure

Students began using the Cognitive Tutor in their math course at the beginning of the academic year. The data examined in this paper come from the third quarter of the academic year. Students first encountered unit-specific versions of the achievement goal measure in January when scales were inserted into units they had yet to complete. They completed tutor units twice a week during math class periods for the duration of the semester. Third quarter grades were assigned in March based on student performance on classroom assignments, homework, quizzes and tests (and *not* completion of or performance in Cognitive Tutor units). We examined tutor data and grades from the third quarter (January through March).

2.4. Data analysis

In order to answer our first research question, we investigated stability and change in achievement goals across units using the differential continuity, mean-level, and reliable change analyses employed in prior research with undergraduate samples (Fryer & Elliot, 2007; Muis & Edwards, 2009). To address our second research question, we examined correlations between the average strength of students' achievement goals and learning behaviors. To test our third research question, we examined the distribution of achievement goal variability scores and, after noting a bimodal distribution for each goal, split the sample into groups of students with stable versus variable achievement goal scores. We then assessed whether students with different levels of variability in task-specific achievement goals would behave differently when completing ITS math units or perform differently in the geometry course.

3. Results

3.1. Stability and change in task-specific achievement goals

3.1.1. Differential continuity

To determine how stable or variable high school geometry students' achievement goals were when learning math in an intelligent tutoring system, we conducted a differential continuity analysis. This method is common in personality research and examines the rank-order stability of a construct across pairs of observations (Caspi, Roberts, & Shiner, 2005). Differential continuity analyses are akin to test–retest analyses and employ Pearson product-moment correlations. Results of this analysis appear in Table 2, with differential continuity scores indicated along the diagonal with bold typeface. The significant correlations indicate a considerable degree of stability with respect to differential continuity for each achievement goal observed. The average correlation between goal scores within a goal and across units (e.g. correlation between mastery approach scores for units 12 and 18) was $r = .58$; correlations ranged from $r = .32$ to $r = .75$.

3.1.2. Mean-level change

We next investigated mean-level change in achievement goals with a series of repeated measures ANOVAs to examine changes in the average score of the sample per achievement goal over time (Caspi et al., 2005). Means for each goal in each unit appear in Table 1. For this sample, mean-level scores did not differ significantly across units, indicating that goals are stable when appraised in this way, (for all F values, $p > .05$).

3.1.3. Individual-level change

We examined changes within individuals' achievement goals using a *reliable change index* (RCI; Christiansen & Mendoza, 1986; Jacobson & Truax, 1991). Reliable change indices were developed to enable researchers who observe variability in a construct over multiple observations to distinguish between instances where variability can be attributed to imperfections in measurement by an instrument versus *reliable* change stemming from actual changes in the construct between observations. To make this distinction, researchers examine the difference in scores by the standard error of the difference score (i.e., the spread of the distribution of change scores to be expected if no change occurred). By comparing this value against a critical value set a priori (i.e., ±1.96), the RCI score can be used to categorized individuals as demonstrating a significant increase (i.e., RCI value > 1.96), a significant decrease (i.e., RCI < −.196), or no significant change across a pair of observations (i.e., between ±1.96). Scores falling outside the range of ±1.96 are unlikely to occur by chance and are thus considered indicative of reliable change.

In our analyses, we compared students' achievement goal scores per unit to one another and summarize the frequency with which students' goal score increased or decreased reliably across pairs of observations in Table 3. When summarizing across students who report reliable increases, decreases, or no reliable change in achievement goals across all combinations of units, we found that approximately one third of students increased in their endorsement of each achievement goal, one third decreased, and one third reported no change in their goals. When aggregated over the entire sample, each of the three achievement goals showed a pattern of change significantly different from what would be expected if change were random. Whereas mean-level analyses suggest that students' achievement goals are generally stable, aggregation across individuals belies considerable variation within individual students over repeated observation. More than half of students demonstrate a reliable change in their achievement goals in each comparison. Consistent with prior research conducted with undergraduates, mean-level data indicates that the average strength of high school students' achievement goals does not change from unit to unit. However, the reality is that the majority of individual students' achievement goals do vary from unit to unit, and that the proportion of students that increase in a goal offsets those that decrease when summarized using mean-level calculations.

3.2. Effect of achievement goal strength on learning

To examine the effect of goal strength on behavior and performance, we examined the correlation of students' average mastery approach, performance approach and performance avoidance score with their learning process in the Cognitive Tutor. These processes include the number of hint requests made per unit (i.e., help

Table 2
Correlations between unit-level achievement goal scores.

	Goal and Unit		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Mastery approach score	Unit 12														
2		Unit 14	**.54***													
3		Unit 16	.26	**.75***												
4		Unit 18	.23	.64*	**.63**											
5		Unit 20	−.27	.10	.27	**.35**										
6	Performance approach score	Unit 12	.45*	.27	.11	.27	−.07									
7		Unit 14	.13	.61*	.68*	.62*	.23	**.36**								
8		Unit 16	.16	.70*	.85*	.60*	.24	.19	**.74***							
9		Unit 18	.19	.69*	.63*	.89*	.30	.22	.68*	**.67***						
10		Unit 20	−.40*	.06	.13	.26	.86*	−.18	.20	.27	**.32**					
11	Performance avoidance score	Unit 12	.24	.16	.30	.35	.13	.52	.47*	.25	.18	.04				
12		Unit 14	.11	.55*	.70*	.60*	.37	.34	.90*	.63*	.61*	.25	**.58***			
13		Unit 16	.22	.76*	.89*	.67*	.35	.14	.69*	.83*	.64*	.29	.32	**.74***		
14		Unit 18	.20	.65*	.62*	.97*	.38*	.25	.66*	.60*	.86*	.29	.45*	.63*	**.67***	
15		Unit 20	−.21	.07	.29	.38*	.94*	−.04	.16	.15	.28	.74*	.21	.35	.36	**.40***

Note. Bold scores on the diagonal represent correlations between subsequent units and correspond to differential continuity analyses.
Values marked with an asterisk represent statistically significant correlations (i.e., $p < .05$) between unit-specific achievement goal scores.

Table 3
Reliable change in achievement goal endorsement.

Goal type	Unit 12–14			Unit 14–16			Unit 16–18			Unit 18–20		
	% Decrease	% No change	% Increase	% dec	% NC	% inc.	% dec	% NC	% inc.	% dec	% NC	% inc.
Mastery approach	35	35	30	38	44	18	38	44	18	20	49	31
Performance approach	45	20	35	29	49	22	29	49	22	27	51	22
Performance avoidance	32	40	28	38	38	24	38	38	24	26	54	20

Note. dec = decrease, inc. = increase, NC = no change.

Table 4
Correlations between achievement goal scores and learning measures.

	Help seeking[a]	Accuracy[b]	Efficiency[c]	Course performance[d]
Average mastery approach goal score	−0.10	0.13	0.01	−0.19
Average performance approach goal score	0.03	0.02	0.15	−0.37
Average performance avoidance goal score	−0.06	0.03	−0.02	−0.19

[a] Hint requests per unit.
[b] Percent of problem steps answered correctly.
[c] Number of problems needed to complete the unit.
[d] Quarter 3 Grade.

seeking), the number of problems required to complete a unit (i.e., efficiency), and the percent of problem steps answered correctly (accuracy). We also examined the effect of achievement goal scores on performance, using third quarter geometry grades as an outcome variable. Correlations appear in Table 4. Analyses indicated that the strength of students' achievement goals were not significantly correlated with their tendency to seek help in the tutor by requesting hints, accuracy on problem steps, or efficiency in completing units, *rs* (28) < .15, *ps* = ns. Average achievement goals scores also failed to correlate significantly with Quarter 3 grades, *rs* (28) < |.37|, *ps* = ns.

3.3. Effect of stability in achievement goals on learning

Our third research question examined whether learners with stable goals would behave or perform differently compared to learners with goals that varied across tutor units. Reliable change analyses indicated that the majority of students' goals' changed from unit to unit, and this phenomenon has been documented in prior research (Fryer & Elliot, 2007; Muis & Edwards, 2009). However, the relationship between variability and learning has yet to be explored. We measured variability in a student's achievement goal endorsement by calculating a standard deviation per achievement goal across their goal scores in the five units. We examined the distribution of variability in students' goal scores and found that, for each goal, a bimodal distribution emerged, indicating subgroups of students that reported either a stable or variable level of the achievement goal. We split the sample accordingly (i.e., at the median, which coincided with the bimodal split) and examined whether students with a stable achievement goal would behave or perform differently from peers whose achievement goal score was more variable.

3.3.1. Goal stability and learning with the Cognitive Tutor

In terms of behavior, learners with variable performance approach goals requested more hints than learners with stable performance-approach goals, t (26) = 2.60, $p < .05$, $d = .98$ (Fig. 2). No differences were found between groups on measures of efficiency or accuracy, t (26) < .5, p = ns. No significant differences were found between learners with stable versus variable mastery approach or performance avoidance goals on help seeking, efficiency, or accuracy (all *ts* < 1.30, p = ns).

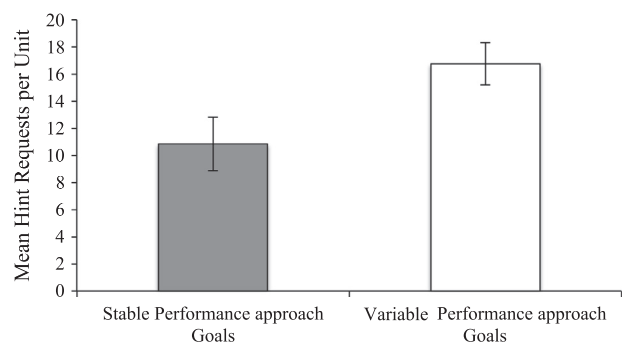

Fig. 2. Mean differences in total hint requests per unit between learners with stable versus variable unit-specific performance-approach goals; *ns* = 14 per group.

3.3.2. Goal stability and course performance

With respect to performance in the geometry course, those with stable mastery approach goals achieved higher third quarter grades than those in the variable mastery approach goal group, t (26) = 2.22, $p = .04$, $d = .84$ (Fig. 3). No differences were found for stable versus variable performance approach or performance avoidance goals, *ts* < 1.10, p = ns. In sum, stability in achievement goals was associated with large effects on both the learning behaviors that individuals conduct and the performances they achieve.

4. Discussion

The primary goals of this study were to examine patterns of stability and change in adolescents achievement goals for mathematics units completed in an intelligent tutoring system and to determine whether achievement goal stability affected learners' behaviors and outcomes. We found that adolescents' achievement goals exhibited similar elements of stability and change to the undergraduate populations observed in prior research (Fryer & Elliot, 2007; Muis & Edwards, 2009). Differential continuity and mean-level analyses indicated that achievement goals were consistent over time and stable when sample means were observed, but individuals' goals changed reliably from unit to unit. The within-student variability in achievement goals detected by reliable change analyses in this and prior research with undergraduates suggest that a single assessment of achievement goals cannot capture variability in a motivational construct like achievement

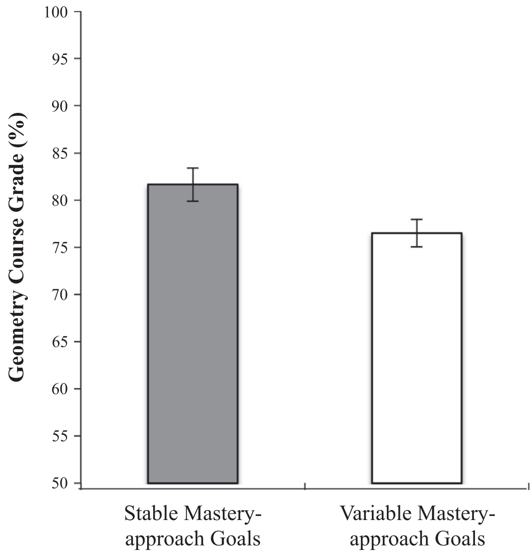

Fig. 3. Mean differences in third quarter grades between learners demonstrating stable versus variable unit-specific mastery-approach goals; *n*s = 14 per group.

goals. In their place, we recommend frequent measurement that can capture both strength and variability in achievement goals, especially in light of our novel findings that variability has implications for learning behaviors and outcomes.

4.1. Effects of goal stability and variability on learning behavior and performance

Though much prior work has examined associations between the strength of achievement goals and learning behavior and performance, few studies employed observational methods to assess behavior, and none have examined the effects of variability in students' achievement goals on learning processes. In order to understand why behavioral and performance differences occurred between learners with stable versus variable goals, we must interpret what it means to have stable or variable achievement goals. One way to interpret the stability of learners' achievement goal endorsement is to assume that those who consistently endorsed an achievement goal either have a goal that is driven by more dispositional characteristics or are less susceptible to situational factors. Conversely, those who demonstrate variable endorsement of an achievement goal are either more influenced by the situation or do not have enduring, consistent dispositions. This interpretation aligns to arguments made by personality theorists about continuity and change in personality variables (Bem, 1974; Mischel, 1968) and assumptions made about the influence of dispositional and environmental factors on goals by achievement goal theorists (Ames, 1992; Dweck, 1999; Elliot & Church, 1997; Elliot & Thrash, 2001; 2002).

So why did students with stable mastery-approach goals outperform those with variable goals? It is possible that those who demonstrate consistency in mastery approach goals across tutor units also maintain these goals outside the tutoring environment. In addition to ITS use, students attended class, used their textbook, and completed other assignments. It is possible that the behaviors that led to superior performance were conducted both in class as well as during tutoring sessions. For example, students who consistently adopt mastery-approach goals across tasks may employ more effective and successful study strategies for homework or learning from in-class lecture and activities. The tutoring environment might especially serve to help those students *without* stable mastery goals who typically do not use these strategies and thereby help them achieve similar performances in tutor units when there is much instructional scaffolding and support. This would also explain the lack of correlation between learning behaviors in the tutor and average mastery goal scores. It is also important to note the minimal variance in accuracy scores presented in Table 1. Because the tutor requires students to accurately answer a problem step before moving onward, students are required to accurately answer each problem step they encounter (though often after incorrect attempts, correctness feedback, and at times, after viewing step-specific hints). This is a useful design feature for prompting desirable learning behaviors like evaluation of feedback and help seeking, but also leads to a range restriction in percent correct, which decreases the likelihood that achievement goals would relate to this measure of immediate performance (as opposed to performance in the course, which was affected by mastery approach goal stability).

With respect to the relationship between goal stability and behavior, those with stable performance approach goals tended to avoid using the tutor's help feature. We know from achievement goal research that students who adopt performance approach goals focus on achieving an optimal performance on a learning task, which in the Cognitive Tutor, would correspond to 100% accuracy on problem steps in a unit. They are also motivated by a desire to outperform their peers. While the Cognitive Tutor lacks a normative reference (i.e., skill meters are based on the criterion of skill mastery), we know from classroom observation that students constantly compare their progress through units with their peers. In this sample, students with stable performance approach goals were consistently concerned with their performance in the Cognitive Tutor and may have been more sensitive to the assessment criteria used by the tutor and adapted their behaviors accordingly. This framing of the task based on tutor criteria and resulting adaptation of behavior conforms to Senko and Miles' (2008) *learning agenda hypothesis*. That is, these students perceived that the tutor makes an assessment of their skillfulness on each step, depending upon whether they get the step correct or incorrect, or ask for a hint. When a step is completed without an error, the student's skill meter moves towards the mastery threshold. When an attempt is incorrect or when a hint is requested, it does not. Thus the mere act of requesting a hint runs counter to the goal of 100% accuracy and fastest possible skill meter increases. In prior work, others have found that students pay close attention to these skill meters and, when prompted to explain how hints affect skill meters, students explain that requesting a hint keeps the skill meters from increasing (Long & Aleven, 2011). If a performance-oriented student perceives hints as barriers to progress on skill meters (i.e., a readily available performance metric), they will avoid using hints. We speculate that those students who were consistently concerned with their performance across tutor units chose to avoid using hints and instead would attempt to increase the likelihood of improving their skill meter readings by venturing an answer, even if the answer was a guess and requesting a hint might have been a more appropriate action. Ignoring the hint features provided by the ITS diminishes the helpfulness of the technology and could influence what is learned from the activity.

To date, theoretical work on achievement goals has yet to explicitly describe how the stability of an achievement goal is thought to affect subsequent learning behaviors or achievement. As a result, our analyses were conducted in an exploratory fashion and took on a systematic approach (i.e. two-group comparisons for goal stability for three achievement goals). Given that we conducted six comparisons, the likelihood of obtaining significant effects due to chance increased with this multiple comparison approach. We would encourage researchers to continue to examine the relationship between goal stability and learning behaviors and outcomes in this and other settings to further our understanding of these relationships.

5. Conclusion

In this study, we observed adolescents' achievement goals for mathematics problem solving tasks and examined how these goals influenced their learning behaviors during problem solving and their achievement in math. Whereas prior work examined undergraduates' achievement goals for psychology exams and assignments, this study extended examinations of stability and change in achievement goals to a new population and context (adolescents studying mathematics). In addition, we examined not only the implications of the strength of one's achievement goals, but also the relationship between the stability of learners' goals and their learning behaviors and outcomes. While it was observed that individuals' goals changed from one learning task to the next, the effects of such variability were not previously known.

These novel findings demonstrate the benefits of pairing frequent self-reports with continuous behavioral assessment for unpacking the relationships between motivation, behavior, and learning outcomes. The findings in this study were obtained using a microgenetic assessment method that involved brief, unit-specific assessments of motivation administered during problem solving (Bernacki et al., 2013). These unit-specific measures possessed similar reliability to course-specific measures and, when administered frequently, provided precise assessments of learners' goals for specific tasks and served as the basis for a measure of goal stability. Moreover, when paired with behavioral data, these unit-specific measures produced novel findings that could not be obtained using more general measurement approaches.

In addition to improving the precision of assessments, the approach we describe better reflects theoretical assumptions about the role of motivation as students self-regulate in complex learning tasks. Motivation and self-regulatory activities such as planning, monitoring, strategy use, and adaptation all form a dynamic system in which all components influence one another (Winne & Hadwin, 2008; Zimmerman, 2011). By using microgenetic self-report methods to assess motivation repeatedly, we can more precisely assess how motivation fluctuates in response to learner characteristics, task conditions, and prior behavior and feedback, which can help explain the future behaviors and outcomes that result. In addition, behavioral methods can be a powerful tool for examining how learning processes mediate the effect of motivation on learning. By logging students' behaviors using learning software and frequently assessing motivation in context, we can better understand learner's task-specific motivations, their influence on learning behaviors, and their relationship to performance.

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