Exploring Changes in Computer Science Students' Implicit Theories of Intelligence Across the Semester

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ABSTRACT

Our study was based on exploring CS1 students' implicit theories of intelligence. Referencing Dweck and Leggett's [5] framework for implicit theories of intelligence, we investigated (1) how students' implicit theories changed over the course of a semester, (2) how these changes differed as a function of course enrollment and students' self-regulation profiles, and (3) whether or not implicit theories predicted standardized course grades and performance on a computational thinking knowledge test. For all students, there were significant increases in entity theory (fixed mindset) and significant decreases in incremental theory (growth mindset) across the semester. However, results showed that students had higher scores for incremental than entity theory of intelligence at both the beginning and end of the semester. Furthermore, both incremental and entity theory, but not semester change in intelligence theory, differed based on students' self-regulation profiles. Also, semester change in entity theory differed across courses. Finally, students' achievement outcomes were weakly predicted by their implicit theories of intelligence. Implications for student motivation and retention in CS and other STEM courses are also discussed.

Categories and Subject Descriptors

K.3.2. **[Computers and Education]**: Computer and Information Science Education

General Terms

Performance, Human factors, Theory

Keywords

Implicit learning theories; CS1; Profiling

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1. INTRODUCTION

Student achievement and retention in science, technology, engineering, and mathematics (STEM) courses have been the focal point of much research. STEM-related fields will grow at nearly twice the rate as opportunities in non-STEM fields between 2008 and 2018 [13]. Additionally, the number of jobs in STEM fields grew at nearly three times the rate as the number of jobs in non-STEM fields during the first decade of the 21st century [13]. However, research has demonstrated that retention rates of students pursuing STEM majors fall short of meeting the workforce's demands. For example, studies have shown that approximately 44% of STEM majors change to a non-STEM major before graduation [21]. As a result, a major concern for post-secondary administrators is increasing the number of students who declare a STEM-related major and retaining those students in the major until they graduate and enter the workforce.

A significant body of literature has investigated the factors that influence achievement and retention in STEM courses and majors [2, 12, 29]. Studies have demonstrated how STEM students' goal orientation [10], quality of instruction received [20], gender [27], strategic self-regulation [21], performance/enrollment in introductory ("gatekeeper") courses [2], and the perceived difficulty and usefulness of STEM courses [16] predict achievement and attrition in undergraduate STEM courses such as Computer Science (CS).

Meanwhile, *implicit intelligence theories* have remained a relatively understudied aspect of students' learning, achievement, and persistence in STEM courses. According to Dweck [4], implicit intelligence theories refer to *peoples' general theories about whether their intelligence is a fixed trait (entity theory) or a malleable quality that can be enhanced through learning and effort (incremental theory)*. Commonly known as fixed (entity theory) and growth (incremental theory) mindsets, Dweck and Leggett's [5] framework for implicit theories of intelligence has received widespread attention in research. Students' implicit theories about their intelligence have been shown to influence the types of goals they pursue [11], persistence in the face of difficulty [15], academic success [1], and attributions for their successes and failures [19]. However, little research has examined changes in implicit intelligence theories across a single semester.

The present study sought to help fill this gap in the literature by exploring changes in CS students' implicit intelligence theories across a semester in an introductory CS (CS1) course. In this study, the profiling approach advocated by several educational researchers was used [17, 25]. In educational research, profile approaches are used to identify distinctly different clusters of students based on their motivation and self-regulated learning behaviors. According to Nelson *et al.* [17], "Using the profile approach, researchers can consider interactions among many independent, well-established psychological constructs" (p. 76). Instead of exploring how individual motivational constructs (e.g., self-efficacy) predict specific outcomes (e.g., course grades) in a piecemeal fashion, profile approaches utilize a multivariate approach to understand students' outcomes. In the present study, changes in students' implicit intelligence theories across the semester were explored as a function of their motivational and self-regulation profile, as well as their gender and the CS1 course in which they were enrolled.

1.1 Implicit Theories of Intelligence

A significant body of literature explores how students' implicit theories about the nature of their intelligence influence their achievement and motivation. Largely, the literature has shown that students of all ages and grade levels can be classified as being either *entity* or *incremental* learning theorists [5, 4]. *Entity theorists* believe intelligence is a fixed entity (i.e., either you are born intelligent or you are not). Entity theorists believe no matter how much time and effort they put into learning, they are bounded by their natural level of intelligence and their intellectual ability cannot be increased through their own efforts [5]. Conversely, *incremental theorists* believe intelligence is a malleable trait that can be enhanced through learning, time, and effort. Incremental theorists believe their intellectual ability can be cultivated and increased through their own efforts [5].

Differential outcomes have been associated with each of these implicit intelligence theories. Students who possess an entity theory about their intelligence tend to focus more on their performance outcomes (e.g., getting a passing grade or appearing smart to one's classmates), attribute failure to a lack of ability, and believe that working hard reflects a lack of ability rather than a commitment to improvement [6]. For entity theorists, poor performance reflects inadequacies in their intelligence; in their eyes, giving a purposeful effort to improve would only confirm their inadequacies to their classmates. Alternatively, incremental theorists set mastery goals geared towards gaining a complete understanding of the course material, believe effort is a means to becoming more intelligent, and view failure as an opportunity for improvement [6]. For incremental theorists, poor performance does not indicate an intelligence inadequacy that cannot be overcome. Instead, with sufficient effort, improvements can be made and performance can be enhanced. Differential performance outcomes have also been associated with being an entity or incremental theorist. Specifically, it has been found that students who possess an incremental theory of intelligence tend to receive higher grades than those who possess an entity theory [1].

Although literature related to implicit intelligence theories in STEM courses remains sparse, a couple of studies exist. Reid and Ferguson [18] found that freshman engineering students demonstrated a non-significant increase in entity mindset from the beginning until the end of their first year. Additionally, they found that implementing a team-based project designed to enhance students' incremental theories in a first-year engineering course caused no significant changes in incremental or entity theories across the school year. A study by Simon *et al*. [26] found that training CS, computer engineering, and non-CS engineering students to adopt an incremental theory of intelligence did not significantly increase students' incremental theories. In summary, the existing STEM and CS literature suggests that these students may have a tendency to shift towards an entity theory of intelligence across the first-year of college. However, this literature lacks significant results. Thus, more research is needed to understand how implicit intelligence theories change for CS (and other STEM) students across time.

The implicit intelligence theories literature suggests that students who believe intelligence in a domain can be enhanced through time and effort tend to experience enhanced levels of motivation and success. Meanwhile, students who believe their intelligence is outside of their control tend to give up in the face of difficulty. The relationship between implicit intelligence theories and persistence in the face of difficulty could inform an approach for increasing retention and enrollment in STEM and CS courses. Exploring changes in STEM and CS students' implicit intelligence theories over time may help educators understand the difficulty in retaining students and how to address it.

1.2 Profile Approach

Although many factors influence undergraduate students' success, these factors have historically been studied individually, in a piecemeal fashion. For example, studies may look at the relationship between students' mathematical self-efficacy and performance on exams or explore the relationship between intrinsic motivation and persistence on difficult tasks. At most, according to Nelson *et al*. [17], studies may look at the way these factors interact, through methods such as a multiple regression or analysis of variance. For example, predicting students' final course grades using their self-efficacy, intrinsic motivation, and goal orientation. An alternative approach to studying students' outcomes is by focusing on the coordinated pattern of specific factors, such as students' motivation and self-regulated learning tendencies.

This was the approach taken by Shell and Husman [24] when they attempted to understand differences in motivation and strategic self-regulation among college undergraduates taking an elective psychology course. In this study, participants completed a battery of measures to assess their self-efficacy for self-regulation, expectancy for success, causal attributions, locus of control, goal orientation, future time perspective, course affect and anxiety, strategic self-regulation, and study time. Five profiles were identified: (a) a *strategic* learner who demonstrates a high level of self-regulation and aspires to master course-content and achieve highly in the classroom, (b) an *apathetic* learner who demonstrates low levels of self-regulation, as well as low levels of mastery and performance orientations, (c) a *knowledge builder* who aspires to master the course content but places less emphasis on utilizing traditional learning strategies, (d) a *surface* learner who sees little value in the course, applies the lowest amount of self-regulation, and seeks to do the minimum amount required to pass a class, and (e) *learned helpless* students who ineffectively attempt to be good students, eventually causing them to lose confidence in their own academic abilities. Recent studies have replicated the presence of these five profiles among undergraduate CS, engineering, and other STEM students taking introductory computer science courses [17, 25].

Profile research has yielded interesting results and discussions for those concerned with STEM education, specifically CS education for purposes of the present study. First, researchers have argued that profile adoption may be course specific [7, 22]. In other words, a student may adopt a more motivated, goal-directed approach in her biology courses, but take a more surface learning approach towards her history courses. For those concerned with CS education, it is important to understand whether or not students possess the motivation and self-regulation necessary to enhance their computational thinking and ability including problem solving via computer programming. Second, some profiles are more adaptive than others. Research has shown that the strategic learning and knowledge building profiles are more adaptive than the other three profiles. For example, students adopting the strategic learning and knowledge building profiles score more highly on achievement measures [17], demonstrate higher mastery goal orientations [10], and see greater value in their CS courses [25] than students adopting the apathetic, surface learning, and learned helpless profiles. Finally, research has found that profile adoption tends to be relatively stable over time, with only one-third of students changing profiles across the course of an academic year [9, 26]. Thus, *it is important for educators to be proactive about impacting the learning orientation students take towards CS courses before students commit to a maladaptive approach to learning CS*.

2. THE PRESENT STUDY

The present study sought to contribute to the CS education community's understanding of the dynamic nature of student learning theories by exploring how CS students' implicit intelligence theories changed across the semester. The central research question guiding this study was: ***Do CS students' implicit intelligence theories change from the beginning to the end of the semester?*** Additionally, the following sub-questions served to compliment the central research question:

1. Do changes in implicit intelligence theories across the semester differ as a function of student profiles (strategic, knowledge building, apathetic, surface learning, and learned helpless) or the CS1 course they are enrolled in?
2. How does change in implicit intelligence theories across the semester relate to students' learning outcomes in CS1 courses?

3. METHODS

3.1 Participants

Participants for this study were 621 undergraduate students (538 males; 83 females) from CS1 courses at a large Midwestern state university. Two hundred and ninety-seven participants were freshmen, 184 were sophomores, 72 were juniors, 51 were seniors, and 17 identified as other. Of these participants, 443 (380 males; 63 females) provided complete data and were included in the profile analysis. The CS1 courses, from which the participants were recruited, catered to different undergraduate student populations: one course consisted of CS majors, one course consisted of engineering majors, one course consisted of a combination of computer, engineering, and physical science majors, one course consisted of humanities majors, and one course consisted of interdisciplinary business-CS honors students.

3.2 Instruments

3.2.1 Implicit Intelligence Theories

Participants' implicit intelligence theories were assessed using the Implicit Theories of Intelligence Scale [4, 30] which contains eight Likert-type items with response options ranging from 1 *(strongly disagree)* to 6 *(strongly agree)*. Two separate four-item scales measure students' incremental theory that intelligence can be increased (e.g., "You can always substantially change how intelligent you are") and their entity theory that intelligence is unalterable (e.g., "You have a certain amount of intelligence, and you can't really do much to change it"). This measure operationalizes intelligence as a general construct and is not specific to CS1 or other courses. For the present study, an alpha level of .92 was obtained for the incremental scale and an alpha level of .91 was obtained for the entity scale.

3.2.2 Profile Measures

For Profile Analysis a battery of assessments of students' motivation and strategic self-regulation were used. Students' motivation was assessed with a battery of instruments consisting of (1) students goal orientation for the class; (2) students' future time perspective consisting of their ratings of the connectedness between their academic coursework and a STEM career and the perceived instrumentality of their specific course work for attaining STEM academic and career goals; and (3) students' emotional/affective reactions to the course. Students' strategic self-regulation was assessed with four scales from the Student Perceptions of Classroom Knowledge Building instrument (SPOCK) that assessed metacognitive self-regulation, knowledge building, question asking, and lack of engagement. Students' study time and study effort also were assessed. Details on these measures can be found in [24, 25, 17]

3.3 Procedures

This study took place as part of a larger NSF-funded study geared towards improving students' abilities to learn computational thinking by incorporating computational and creative thinking exercises into undergraduate CS courses [14]. Participants completed the beginning of the semester Implicit Theories of Intelligence Scale, future time perspective measures, and additional assessments not used in this study during lab or lecture sessions during the first week of the semester. End of semester surveys were done in lab or lecture sessions during the last two weeks of the semester. Participants repeated the beginning of semester instruments, except for the connectedness scale, along with the SPOCK, emotion/affect, and studying measures and additional scales to assess their computational thinking knowledge and to evaluate the course activities. All of the surveys were completed using the Survey Monkey® online survey tool.

3.4 Analysis Procedures

All data analysis was performed using SPSS v. 21 and 22. ANOVA were done using the General Linear Model repeated measures procedure. Regression was done using the linear regression procedure. Profile analysis was done using the two-step cluster analysis procedure.

4. RESULTS

The present study explored (a) whether CS1 students' implicit intelligence theories changed across the course of the semester, (b) the factors that potentially mediate changes in students' implicit intelligence theories (e.g., student profile, gender, and

Table 1. Five Profile Solution

	Strategic	Knowledge Building	Surface Learning	Apathetic	Learned Helpless
SPOCK Self-Regulation	3.84	3.02	3.38	2.32	3.31
SPOCK Knowledge Building	3.70	2.89	2.72	1.87	3.20
SPOCK Lack of Regulation	2.62	2.63	3.25	3.20	3.06
SPOCK High-Level Question Asking	3.50	2.30	2.57	1.67	3.20
SPOCK Low-Level Question Asking	3.44	2.28	2.89	1.85	3.23
Study Time	3.80	2.60	4.68	2.43	3.04
Study Effort	3.33	2.87	3.67	2.63	2.81
Learning-Approach Goal Orientation	4.57	4.15	3.48	3.45	3.20
Learning-Avoidance Goal Orientation	2.03	2.33	3.78	3.55	2.84
Task-Approach Goal Orientation	4.69	4.54	4.66	4.26	3.21
Task-Avoidance Goal Orientation	2.05	2.53	2.86	3.28	2.83
Performance-Approach Goal Orientation	3.33	3.14	2.98	2.39	2.76
Performance-Avoidance Goal Orientation	2.72	2.98	2.91	2.74	2.90
Endogenous Instrumentality	4.42	3.82	2.54	2.50	3.22
Exogenous Instrumentality	1.71	2.03	3.60	3.37	3.01
Future Time Perspective Career	4.23	4.14	4.19	4.01	3.82
Positive Affect	3.82	3.04	2.56	2.21	2.83

course enrollment), and (c) how changes in implicit intelligence theories could be used to predict course achievement, as measured by standardized course grades and computational thinking knowledge-test scores. Changes in sample sizes reflect changes in the number of participants who provided relevant data at each time point.

4.1 Profile Analysis

Profile analysis was conducted following methods used in [25, 17]. A five-cluster solution (Table 1) was identified consistent with the strategic, knowledge building, apathetic, surface learning, and learned helpless profiles found previously [24, 25, 17]. As in these previous studies, alternative three-, four-, and six-cluster solutions were examined and both aggregate fit indicators and theoretical interpretability favored the five-profile solution.

4.2 Do CS students' implicit intelligence theories change from the beginning until the end of the semester in CS1 courses?

To determine whether participants' fixed theories changed from the beginning to the end of the semester, a repeated measures ANOVA was conducted. Overall for all participants, their entity theory increased significantly from the beginning of the semester until the end (Wilks' λ=.987, F(1, 440)=5.602, *p*=.018, partial Eta^2=.013). Entity theory scores increased from a mean of 2.62 at the beginning of the semester to 2.81 at the end. A second repeated measures ANOVA was conducted to determine whether participants' incremental theories changed from the beginning to the end of the semester. Overall for all participants, incremental theories decreased significantly from the beginning of the semester until the end (Wilks' λ=.971, F(1, 440)=13.101, *p*<.001, partial Eta ^{2}=.029). Incremental theory scores decreased from a mean of 4.28 at the beginning of the semester to 4.05 at the end. Taken altogether, these findings suggest that students' implicit intelligence theories change significantly over the course of a semester. Interestingly, participants' theories that intelligence is a fixed, unalterable entity increased over the course of the semester while their theories that intelligence can be grown incrementally decreased.

4.3 Do changes in implicit intelligence theories differ as a function of student profile and/or course enrollment?

Mixed ANOVA was used to test whether changes identified in students' entity intelligence theory differed as a function of profile cluster. As shown in Table 2, entity intelligence theory was significantly different across different profiles (*F*(4, 436)=5.263, *p*<.001, partial Eta^2=.046); however, the interaction between profile and change across the semester was not significant (*F*(3,436)=1.713, *p*=.146, partial Eta^2=.015) indicating that across semester change in entity intelligence theory was not affected by profile membership.

Table 2. Changes in Entity Theory

		Beginning of Semester		End of Semester	
	N	***M***	***SD***	***M***	***SD***
Profile	441	2.62	1.08	2.74	1.12
Strategic	132	2.38	1.08	2.49	1.16
Knowledge Building	98	2.54	0.98	2.69	1.13
Apathetic	70	2.75	1.22	2.70	1.10
Learned Helpless	54	2.79	0.87	3.21	0.89
Surface Learning	87	2.90	1.09	2.93	1.08
Course	435	2.63	1.08	2.75	1.12
CS majors	68	2.65	1.24	2.58	1.23
CS/PS majors	107	2.79	1.16	2.80	1.19
Engineering majors	205	2.58	0.98	2.70	1.04
Business/CS Honors program	55	2.50	1.03	3.01	1.10

A second mixed ANOVA was used to test whether changes identified in students incremental intelligence theory differed as a function of profile cluster. As shown in Table 3, incremental intelligence theory was significantly different across different profiles (F(4, 436)=7.354, p<.001, partial Eta^2=.063); however, the interaction between profile and change in incremental intelligence theory across the semester was not significant (F(3,431)=2.079, p=.102, partial Eta^2=.016) indicating that across semester change in incremental intelligence theory was not affected by profile membership.

Mixed ANOVA was used to test whether changes identified in students' entity intelligence theory differed as a function of course enrollment. As shown in Table 2, entity intelligence theory was not significantly different across different courses (F(3, 431)=.817, p=.485, partial Eta^2=.006); *however*, the interaction between course enrollment and change in entity theories was significant (F(3, 431)=3.634, p=.013, partial Eta^2=.025; see Figure 1), indicating that change in entity intelligence theory across the semester was different in different courses. An analysis of simple main effects revealed that students in the honor's CS1 course started the semester with the lowest entity theory scores and finished the semester with the highest entity theory scores.

Mixed ANOVA was used to test whether changes identified in students' incremental intelligence theory differed as a function of course enrollment. As shown in Table 3, incremental intelligence theory was not significantly different across different courses (F(3, 431)=2.311, p=.076, partial Eta^2=.016). Also, the interaction between course and change in incremental intelligence theory across the semester was not significant (F(3,431)=2.079, p=.102, partial Eta^2=.014).

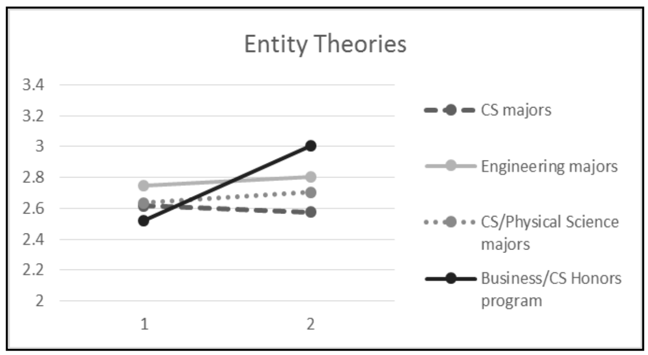
Table 3. Changes in Incremental Theory

		Beginning of Semester		End of Semester	
	N	***M***	***SD***	***M***	***SD***
Profile	441	4.29	1.02	4.12	1.09
Strategic	132	4.63	0.92	4.42	1.02
Knowledge Building	98	4.28	0.93	4.14	1.15
Apathetic	70	4.12	1.19	4.18	1.07
Learned Helpless	54	4.17	0.81	3.77	0.84
Surface Learning	87	4.01	1.10	3.83	1.14
Course	435	4.29	1.02	4.12	1.09
CS majors	68	4.48	1.09	4.44	1.12
CS/PS majors	107	4.14	1.14	4.03	1.15
Engineering majors	205	4.27	0.93	4.09	1.04
Business/CS Honors program	55	4.42	0.96	3.96	1.03

4.4 Do changes in implicit intelligence theories predict CS1 course learning outcomes?

Multiple linear regression analysis was used to examine the relationships between participants' initial intelligence theories, the change in their theories across the semester, and course achievement (as measured by standardized final course grades). Changes in theories were calculated by subtracting participants' beginning of semester scores from their end of semester scores, so that positive values indicate a strong endorsement of the theory at the end of the semester. The overall model was significant (R^2=.025, F(4, 430)=2.741, p=.028). Initial incremental theory (β=-.253, t=-2.862, p=.004) and change in incremental theory (β=-.135, t=-2.017, p=.044) were both significant predictors of students' standardized course grades. This indicates that the theory that intelligence can be incrementally developed over time has significant implications for CS students' final grades. Taken together, it appears students' initial incremental theories about intelligence and the degree to which those theories change across the semester are significantly related to course grades. However, contrary to prior research [18], having an incremental theory of intelligence and increasing in belief in an incremental theory of intelligence both were associated with lower course grades. No significant relationships were found for their initial entity theory or the change in entity theory across the semester.

Figure 1. Change in Entity Theory by Course



A parallel analysis was conducted using computational thinking knowledge-test scores as the criterion variable. The overall model was significant (R^2=.023, F(4, 409)=2.431, p=.047). Only initial entity theory (β=-.185, t=-2.032, p=.043) and initial incremental theory (β=-.217, t=-2.403, p=.017) were significant predictors. These findings suggest that the theories about intelligence students possess when they enter into a CS1 course has a significant relationship with their learning of computational thinking knowledge and skill during the semester. Although entity theory, as expected from prior research and theory [1, 4], predicted lower learning, incremental theory, contrary to expectations [1, 3], predicted lower learning.

5. DISCUSSION

5.1 Grand Summary of Findings

Our results indicate that the implicit intelligence theories of undergraduate CS1 students change across the semester. These findings differ from conventional literature that posits the stable nature of implicit intelligence theories across time [19].

First, *regardless of student profile, incremental theory decreased from the beginning until the end of the semester*. Interestingly, although the decrease in incremental theories was significant for all participants, significant decreases were only detected for the Strategic and Learned Helpless profiles. For the Learned Helpless profile, this change seems comprehensible. These students apply themselves in a purposeful effort to self-regulate their learning, but struggle to do so effectively. As a result of the incongruence between effort and achievement, these students may "lose faith" that their learning outcomes are a result of their effort. For the Strategic Learners, this decrease is more perplexing. This profile is typified by high levels of motivation, effective learning strategies, and achievement. Why these students come to view their intelligence as less malleable over the course of a semester warrants future investigation. However, a tentative explanation does exist. Perhaps the strategies employed in other courses do not readily translate to success in CS courses. If this explanation is correct, then perhaps Strategic Learners who enter into CS courses have their incremental theories challenged by the difficulty of transferring their learning strategies into CS.

Second, *regardless of student profile, entity theory increased from the beginning until the end of the semester*. Similar to the change in incremental theory from beginning until end of the semester, the increase in entity theory was significant for all participants overall, but a significant increase was only detected for the Learned Helpless profile. Again, based on the characteristics of this profile, the change makes sense. As the Learned Helpless begin to see their efforts as futile, they may begin to view intelligence as less malleable and more as a pre-determined trait outside of their control.

However, it is important to note that, overall, CS1 students began the semester scoring highly on incremental theory of intelligence (M= 4.29). Furthermore, CS1 students scored more highly on incremental than entity theories of intelligence at both the beginning and end of the semester. Thus, even though incremental theory decreased and entity theory increased throughout the course of the semester, *incremental theory was still more strongly endorsed by CS1 students across the semester*. These findings suggest that promoting incremental theory of intelligence in CS1 students should *not* be CS educators' main concern. Instead, CS educators should concern themselves with helping their students sustain their belief in the implicit theory that intelligence is a malleable trait within one's own control.

Third, *course enrollment was related to students' implicit intelligence theories across the semester*. Specifically, students in the CS1 course offered to members of a prestigious honors program for business and CS double-majors exhibited significant changes in their incremental and entity theories from the beginning until the end of the semester. These students tended to be more motivated and higher achieving than the students in other CS1 courses. However, the pattern of change experienced by these students matched the general pattern for all students (increased entity theory and decreased incremental theory), but this group had the greatest increase in entity theory. So, even for students with the highest levels of motivation and achievement in our sample, their theories of intelligence still shifted away from a malleable trait and more towards a fixed entity. A potential explanation for this shift may exist. Honors students are used to experiencing high levels of academic achievement, which may lead them to attribute their success to being a "smart" person. As a result, their high performance in CS1 and other courses may only serve to confirm their theory that intelligence is a fixed entity—an entity which they possess. Future research is warranted to explore this tentative explanation.

Finally, implicit intelligence theories weakly predicted standardized final course grades and performance on an end-of-semester computational thinking knowledge test. *Decreases in incremental intelligence theory were associated with higher standardized course grades*. This is opposite of what is expected for incremental theory, but may be due to range restriction. Most students scored highly on incremental theory, but a large drop in incremental theory in a few high achieving students could strongly impact the statistical relationship between intelligence theories and course achievement. This is what occurred with the honors course: the most successful students experienced the largest decrease in incremental theory from beginning to end of the semester. These students still scored more highly on incremental than entity theories, but scored so highly at the beginning of the semester there was seemingly nowhere else for their score to go but down. Thus, the relationship between intelligence theories and standardized course grades may have been distorted. Additionally, the relationship between intelligence theories and achievement was weak. Although previous research has detected more pronounced relationships between students' implicit intelligence theories and grades [1], the present study only found a weak relationship between implicit theories and performance outcomes (final standardized course grades and computational thinking knowledge test). At least for CS1 courses, the present study suggests that *the relationship between implicit intelligence theories and performance outcomes may be weaker than previous research suggests*.

5.2 Implications for CS Educators

STEM educators have long been concerned with attracting and retaining students in STEM-related majors [21, 29], including CS educators. Given this concern, it is important for educators to be aware of the pitfalls associated with students' entity theories of intelligence. As has been noted, possession of an entity theory of intelligence reduces motivation, performance, and the desire to give purposeful effort when attempting to learn or overcome an obstacle [6]. Given the difficult nature of CS courses, research [1, 8] suggests that students who possess an entity theory of intelligence and do not view themselves as "naturally intelligent" may be in danger of giving up in the face of difficulty, withdrawing from CS courses, and switching to a different major.

The present study found that students' inclinations towards an entity theory of intelligence increased over the course of a semester, a finding that has important implications for CS educators and students. While literature has shown that setting performance and mastery approach goals [10], persisting in the face of difficulty [16], and academic achievement [2] are all positively associated with retention in CS and other STEM courses, possessing an entity theory of intelligence is associated with a decrease in all of these factors influencing retention [1, 11, 20]. Thus, *it is important that CS educators explore the relationship between entity theory of intelligence, and persistence in CS related courses, and investigate the impact that this can have on subsequent enrollment*. Better understanding would allow CS educators to better design their courses, assignments, and other activities to check students' conceptual models about intelligence and learning.

Fortunately, CS educators have tools at their disposal to help students maintain the high levels of incremental theories they possess at the outset of the semester. First, research has shown how the type of praise and feedback educators provide to their students impacts the theories of intelligence their students adopt. Specifically, Mueller and Dweck [15] demonstrated how praising students' intelligence (e.g. "You're a very smart student when it comes to reading code.") can actually diminish their motivation and performance. Additionally, students who receive intelligence-based praise or feedback may be more likely to view intelligence as a fixed entity (e.g. "The instructor focused her feedback on intelligence. This must be something either I have or I don't have"). Instead of providing intelligence-based praise or feedback, these researchers found that focusing on effort (e.g., "You did great work. I can tell you applied yourself on this assignment.") enhanced students' performance, motivation, and incremental theories of intelligence. For CS educators, centering praise or feedback on effort may help to combat against the growth of entity theories across the course of the semester and help students sustain their initial incremental theories of intelligence. Second, [3] advocated that instructors emphasize how meaningful learning often takes an extended period of time. Instead of creating a classroom atmosphere where immediate mastery of content is expected, Dweck [3] suggests that instructors instill within students the mindset that it often takes time to understand information at a deeper level. Doing so would allow CS students to understand that just because they do not "get it" right away does not mean they lack intelligence. Rather, deep learning often takes an extended period of time and they can "get it" with more time and effort. Research suggests that creating such a climate in CS classrooms can enhance students' performance, motivation, and incremental theories of intelligence.

6. CONCLUSION

Our findings contrast with existing literature that posits implicit intelligence theories as stable across time [19] and significant predictors of students' learning outcomes [1]. Rather, we found students' implicit theories change from the beginning to the end of the semester, in introductory CS courses included in our study. Although students' scored more highly on incremental theories of intelligence at the beginning and end of the semester, these implicit theories were decreasing. Meanwhile, students' implicit theories that intelligence is a fixed, unalterable entity increased across the semester. Both students' entity and incremental intelligence theories were different across different motivated self-regulatory profiles; but change during the semester in these was not different across profiles. Although both incremental and entity theories of intelligence did not differ as a function of the course the student was in, change in entity theory of intelligence across the semester was different in different courses. This suggests that at least some aspects of students' implicit intelligence beliefs are impacted by what occurs in the classroom during the course. Implicit intelligence theories were only weakly predictive of achievement outcomes. Both initial incremental theories of intelligence and the change in incremental theories of intelligence were predictive of standardized course grades, whereas initial incremental and entity theories of intelligence were predicative of computational thinking knowledge test scores.

Given the emphasis placed on increasing retention in STEM-related (including CS) courses [2] we believe it is important for CS educators to understand the pitfalls commonly associated with the theories that one's own intelligence and learning capabilities are largely stable and outside of his or her control. By incorporating instructional practices into their courses to combat against the growth of entity theories of intelligence and taking steps to help students maintain their incremental theories of intelligence, CS educators may be able to positively impact student motivation, achievement, and retention in CS courses and computing-related majors.

Future research is needed to identify (a) why changes in implicit theories of intelligence occur across the semester, (b) how changes in implicit intelligence theories impact subsequent enrollment in CS (and STEM) courses, (c) the relationship between implicit theories and retention in CS majors, and (d) whether similar shifts in implicit intelligence theories across the semester occur in other STEM courses and majors aside from introductory-level computer science.

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