# Students' Initial Course Motivation and Their Achievement and Retention in College CS1 Courses

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## ABSTRACT
The goal of this study was to investigate how students' entering motivation for the course in a suite of CS1 introductory computer science courses was associated with their subsequent course achievement and retention. Courses were tailored for specific student populations (CS majors, engineering majors, business-CS combined honors program). Students' goal orientations (learning, performance, task), perceived instrumentality (endogenous, exogenous), career connectedness, self-efficacy, and mindsets (growth or fixed) were assessed at the start of the course. Grades were significantly predicted from entering motivation; but prediction was highly variable across courses, ranging from not predicted for the engineering courses to highly predictable for the business-CS honors program. Course withdrawal was significantly predicted. Likelihood of withdrawing was decreased by future time career connectedness and learning approach goal orientation and increased by having an incremental theory of intelligence. Findings suggest that CS1 students who set learning approach goals for their classes have better academic outcomes and higher retention. Other motivational beliefs were inconsistent in their impacts and varied by course and student population. Except for students in an honors program, entering motivational beliefs weakly predicted achievement and retention, suggesting that impacts of the course itself on motivation and how motivation changes during the course are perhaps more important than student's initial motivation.

## Keywords
Student motivation; Goal orientation; Retention; CS1 Achievement.

## 1. INTRODUCTION
In today's rapidly advancing technological environment, the need to attract and retain students in STEM majors is greater than ever before [22, 30]. Career opportunities in STEM-related fields are expected to grow at nearly twice the rate as non-STEM fields between 2008 and 2018 [22]. The need for more post-secondary students to major and graduate in STEM fields, especially computer science (CS), is widely recognized, [4, 22] and there is increasing need for computational thinking in CS and across the broader spectrum of STEM and non-STEM disciplines [29].


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To address these needs, considerable effort has been focused on attracting and retaining students in CS. These include efforts to engage and motivate non-CS majors [7]; instructional strategies such as pair programming, peer-based instruction, and media computation [21]; using personal robots [16]; project-based instruction with different tracks [10]; and framing an appropriate classroom climate to reduce student anxiety about their status among peers and encourage them to co-learn and speak up in class [3]. But, despite these efforts, enrollment and persistence in CS continues to be problematic, with enrollments actually declining over the past decade [18].

This lack of progress indicates a need to better understand the motivations of students who are taking CS courses and how their motivation is contributing to their success and retention. Our purpose in this study was to investigate how students' motivation at the start of an introductory CS1 course was associated with their subsequent course achievement and retention.

## 2. THEORETICAL FRAMEWORK
Prior research has identified important aspects of motivation that are associated with academic achievement, engagement, and strategic self-regulation. These include goal orientation [9, 23, 24], future time perspective (FTP) [12, 13, 14], implicit intelligence or mindsets theory [5], and self-efficacy [2, 8].

In this study, we used a framework proposed by Shell et al. [24, also, 9, 19, 28] that examines course goals in three dimensions (learning, performance, and task) with each dimension having an approach and avoid component. Learning-approach goals are goals directed at learning new knowledge or gaining competence consistent with most past formulations of learning or mastery goals [23, 24]. Learning-avoid goals are deliberate goals to avoid learning of course material. Performance-approach goals reflect a desire to obtain favorable judgments of one's abilities by others or perform better than others in the class; whereas, performance-avoid goals reflect the desire to avoid negative judgments of one's ability or perform worse relative to others in the class. Task- or work-avoid goals reflect a desire to get through the class with as little time and effort as possible [19, 27, 28]. Task-approach goals reflect wanting to perform well on course assignments and tests [9, 19, 24, 28]. They differ from performance goals because they are about doing well without reference to normative performance or gaining positive or avoiding negative evaluations evaluation of competence. They also differ from learning goals in that students can have a goal to "do my work to the best of my ability" without any expectation that they will learn anything.

Studies in CS have found that learning (also known as mastery) approach goals were associated with higher achievement and retention, whereas, performance goals lead to lower achievement

[25] regardless of instructional approach (lecture vs peer instruction) [31]. Other studies in CS1 classes have shown that these goals change across the semester and that increase in task approach and decrease in learning avoid goals are associated with higher achievement and increase in learning approach goals is associated with higher metacognitive strategy use and deep learning [9].

Future time perspective (FTP) is a set of psychological constructs that together explain some differences in students' tendency to plan for the future, delay gratification, and make responsible life choices [13]. Connectedness refers to the ability to make connections between present activities and some future goal [14, 27]. Perceived Instrumentality (PI), is a person's perception of how useful a present task is for a future goal [12, 13]. In the school context, endogenous instrumentality reflects instrumentality of the course content for achieving personally meaningful future goals and outcomes. Exogenous instrumentality reflects a utilitarian connection between course grades and future goals. Students with high perceived instrumentality can see the connection between their current class activities and their more distant future academic, career, and life goals leading to increased motivation for their present learning in school [12, 13, 25]. Studies in CS classrooms have found that higher endogenous instrumentality is associated with higher achievement and exogenous instrumentality is associated with lower achievement, metacognitive strategies, and deep learning [25]

Implicit intelligence theories or mindsets have been shown to impact students' goals, motivation, and achievement [5]. Students who believe in a growth mindset that intelligence is malleable set learning goals, achieve better, and engage in better strategic self-regulation. Students who believe that intelligence is fixed and unchangeable are more likely to set performance-avoid goals and be at risk for learned helplessness [5]. Research has found that 50% of students in engineering fields had a fixed view of intelligence [11]. Studies in CS1 classes have found that growth mindset is associated with more and fixed mindset with less deep learning [25]. Also, both higher growth and fixed mindsets changed across the semester and were associated with lower achievement, contrary to expectations about growth mindsets [6].

Self-efficacy is defined as a person's subjective confidence in their capability of executing an action [2, 24]. Self-efficacy has been consistently identified as one of the most powerful motivators of human action. In a comprehensive synthesis of over 800 meta-analyses [8], it was identified as the strongest predictor of educational achievement. Studies have identified self-efficacy or similar confidence beliefs as key contributors to student choice of major and retention [2].

# 3. CURRENT STUDY

The goal of this study was to investigate how students' entering motivation was associated with their course achievement as measured by course grades, and their retention in the course. Prior research has found that students' motivation in introductory CS1 courses is associated with their course achievement and learning [9, 19, 25, 28]. Studies have shown that goal orientation and mindsets change across the semester [6, 9]. This prior work has looked primarily at during class motivation; it has not examined the goal orientations and motivation of students at the start of the class in-depth.

There are two reasons for looking at students' initial motivation for the course. *First*, students' initial motivation tells us something about why they chose to take the class. This can be important for attracting more students to CS and other STEM courses and majors. Knowing more about the motivation of students who take CS classes can help with targeting recruitment and promotion to students' motivational predispositions. *Second*, if poor performance and withdraw can be linked to students' initial motivation, it may be possible to identify students who are at risk by looking at their motivation at the beginning of class. That could allow instructors to potentially intervene earlier and to tailor interventions based on students' motivational characteristics.

# 4. METHODS

## 4.1 Participants

Participants were 274 students out of 305 total enrollees who consented to participation (229 men; 45 women; 153 freshmen, 62 sophomores, 30 juniors, 19 seniors, 10 other/unknown) from four courses in a suite of required introductory computer science courses (CS1) at a large Midwestern state university. Courses included one for CS majors (CSCE155A, 67 men, 9 women), one for a combined business/computer science honors program (RAIK183H, 20 men, 12 women), one for engineers with content tailored for engineering (CSCE155N, 60 men, 18 women), and one for a mix of computer engineering, other engineering, and general science majors (CSCE155E, 82 men, 6 women). Core content was the same for all courses, but courses were tailored for the different majors with different programming languages, lab exercises, and programming assignments. The study was approved by the University of Nebraska-Lincoln Institutional Review Board (IRB Number: 20120111818EP).

## 4.2 Measures

Further validation information for all goal orientation and motivation measures can be found in [5, 9, 12, 14, 19, 25, 26, 27, 28].

### *4.2.1 Goal Orientation*

Students' course goal orientation was measured with an instrument used in prior studies [9, 19, 25, 28]. *Learning-approach goal orientation* (3 items) assesses goals for developing long-term, deep understanding of information and skills learned in the course (e.g., "Learning new knowledge or skills during the class just for the sake of learning them"). *Learning-avoid goal orientation* (3 items) assesses deliberate avoidance of long-term learning or retention of course information ("Getting a grade whether you remember anything beyond that or not"). *Performance-approach goal orientation* (3 items) assesses normative performance relative to other students and favorable assessments of ability by the instructor for ego protection (e.g., "Doing better than the other students"). *Performance-avoid goal orientation* (3 items) assesses avoiding negative performance evaluations and unfavorable assessments of ability by others (e.g., "Keeping others from thinking I am dumb"). *Task-approach goal orientation* (3 items) assesses efforts to achieve highly and do well on class assignments and activities without reference to normative comparisons (e.g., "Doing my best on course assignments and tests"). *Task-or work-avoid goal orientation* (3 items) assess deliberate intention to put forth minimal effort in the course (e.g., "Getting through this course with the least amount of time and effort"). Students rated goals on a 5-point Likert scale from 1 (*very unimportant*) to 5 (*very important*). Scores were computed as the mean score of the items in each scale. Cronbach alpha estimates were .73, .76, .71, .82, .82, and .77 for the learning approach, learning avoid, performance approach, performance avoid, task approach, and task/work avoid scales respectively.

### 4.2.2 Future Time Perspective

Future time perspective was measured by two instruments. *Career Connectedness* (11 items) assesses connections between a student's present and their future career goals (e.g., "One should be taking steps today to help realize future career goals; What will happen in the future in my career is an important consideration in deciding what action to take now) [14, 19, 27, 28]. Students indicated their agreement with each question using a 5-point Likert scale as follows: 1 (*strongly disagree*) to 5 (*strongly agree*). The career connectedness score was computed as the mean of the 11 items in the scale, with negative items reverse scored. Cronbach's alpha reliability estimate for the scale was .89.

*Perceived instrumentality* was measured with the Perceptions of Instrumentality Scale [12, 25, 28]. The scale measures both endogenous instrumentality (4 items; e.g., "What I learn in this CS1 will be important for my future occupational success") and exogenous instrumentality (4 items; e.g., "The only aspect of this class that will matter after graduation is my grade"). Students indicated their agreement with each question using a 5-point Likert scale from 1 (*strongly disagree*) to 5 (*strongly agree*). Scores are computed as the mean of the items in each scale. Coefficient alpha estimates for the endogenous and exogenous scales were respectively .91 and .91

### 4.2.3 Mindsets

Students' mindsets were measured with the Implicit Theories of Intelligence Scale [5]. The scale measures growth mindset (4-items; e.g., "No matter how much intelligence you have, you can always change it quite a bit") and fixed mindset (4-items; e.g., "You can learn new things, but you can't really change your basic intelligence"). Students indicated their agreement with each question on a 6-point Likert scale from 1 (*strongly disagree*) to 6 (*strongly agree*). Scores are computed as the mean of the items in each scale. Coefficient alpha reliability estimates for the incremental and entity scales were respectively .94 and .89.

### 4.2.4 Self-Efficacy

Students' self-efficacy was assessed using a questionnaire from [26]. Students were asked to rate their confidence in their knowledge of 12 computational thinking and CS topics with emphasis on application in their chosen field and enhancing creativity in their field ("Your ability to use computational algorithms to solve problems in your field;" "Your ability to conceptualize data in your field in ways that can be analyzed computationally"). Questions were based on the specific knowledge and skills taught and used during the CS1 courses. Ratings were done on a scale from 0 (*Completely Unconfident*) to 100 (*Completely Confident*). Self-efficacy scores were computed as the mean of the 12 items. The Cronbach's alpha reliability estimate was .94.

### 4.2.5 Student Grades and Retention

Students' course grades were obtained from University records. To standardize grades across courses, grades were converted to Z-scores within each course. Student retention was indicated by whether a student withdrew from the course.

## 4.3 Procedures

Data was collected during the first week of the fall 2014 semester in either course lecture sessions or course lab periods. All motivation measures test were administered on the Survey Monkey® Web platform.

# 5. RESULTS

## 5.1 Students' Entering Motivation

Mean scores for motivational variables are shown in Table 1. In relation to what are typically considered positive motivational orientations to these goals and beliefs [1, 2, 5, 13, 23, 24, 28], students in these CS1 classes as a group are approaching their class with highly positive motivation. They have high learning approach and task approach goal orientations with correspondingly low levels of learning and task avoid goal orientations. They also express moderate levels of performance approach and avoid goal orientations. They have high endogenous perceived instrumentality and low exogenous perceived instrumentality, along with high career future time connectedness. They express high incremental theory of intelligence and low entity theory. They express low self-efficacy but this is likely an accurate reflection of their computational thinking skills as this is their first college CS course.

Despite these generally positive motivations, there were significant differences in beliefs across the four courses. One-way ANOVA were done for each of the motivational variables. Results for these are indicated in Table 1. The most relevant differences are between the CSCE155N course for engineers and the other three courses. The other three courses are generally part of the students' major field or taken optionally because of the language used (C++ in the CSCE155E course). For the engineers in CSCE155N, the course is more like a foundational course that is not directly a part of their major [19]. Perhaps as a consequence of this not being directly in their major, these CSCE155N students express significantly lower learning approach goal orientation and endogenous instrumentality with correspondingly higher learning avoid goal orientation and exogenous instrumentality. They also have the lowest self-efficacy.

## 5.2 Prediction of Students' Course Grades

Multiple regression was used to predict students' within-course Z-score standardized grades. Because of the number of variables, a backward selection method was used to identify significant predictors. Regressions were done for all students combined and for each course separately because of differences between courses in motivational beliefs (Table 1). For all students, the regression for the final model was significant (R = .244, $R^2$ = .059, $F(4, 242)$ = 3.82, $p$ = .005). Significant predictors were performance avoid goal orientation (β= .113), learning approach goal orientation (β = .198), endogenous PI (β = -.238) and exogenous PI (β = -.188).

There was considerable difference across the four courses. For CSCE155A, the course for CS majors, the final regression model was significant ($R$ = .396, $R^2$ = .156, $F(5, 68)$ = 2.52, $p$ = .037). Significant predictors were self-efficacy (β = -.258), fixed mindset (β = .270), performance avoid goal orientation (β = .217), endogenous PI (β = -.263), and exogenous PI (β = -.343). For CSCE155E, the course for a mix of computer engineering, other engineering, and science majors, the final regression model was significant ($R$ = .282, $R^2$ = .080, $F(2, 72)$ = 3.12, $p$ = .05), The only significant predictors were learning approach goal orientation (β = .340) and endogenous PI (β = .-.232). For CSCE155N, the course for engineers, no model achieved significant prediction (all variables: $R$ = .324, $R^2$ = .105, $F(11, 58)$ = 0.618, $p$ = .806), Although the prediction for CS majors in the CSCE155A was somewhat strong, prediction for the mixed course was marginal and prediction for the engineering majors was not present.

**Table 1. Mean Scores of Variables and ANOVA Results**

| | All Students | | CCE155A | | CCE155E | | CCE155N | | RAIK183H | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Variables** | ***M*** | ***SD*** | ***M*** | ***SD*** | ***M*** | ***SD*** | ***M*** | ***SD*** | ***M*** | ***SD*** |
| Course Grade | 2.78 | 1.25 | 2.38 | 1.46 | 2.67 | 1.38 | 3.20 | .83 | 2.99 | .87 |
| FTPS Career* | 4.07 | .57 | $4.18_{a}$ | .49 | $3.91_{a}$ | .62 | 4.10 | .54 | 4.15 | .57 |
| Self-Efficacy* | 49.49 | 19.24 | 50.87 | 19.57 | 48.20 | 19.36 | $46.18_{a}$ | 18.36 | $57.83_{a}$ | 18.34 |
| Learning Approach GO* | 4.51 | .59 | $4.65_{a}$ | .41 | $4.59_{b}$ | .55 | $4.24_{a\,bc}$ | .73 | $4.63_{c}$ | .46 |
| Learning Avoid GO* | 2.11 | .83 | $1.86_{a}$ | .77 | $2.07_{b}$ | .84 | $2.52_{a\,bc}$ | .76 | $1.83_{c}$ | .76 |
| Performance Approach GO | 3.22 | .83 | 3.33 | .81 | 3.22 | .97 | 3.09 | .73 | 3.26 | .64 |
| Performance Avoid GO | 2.85 | .99 | 2.90 | .99 | 2.78 | 1.02 | 2.82 | .94 | 2.98 | 1.07 |
| Task Approach GO | 4.64 | .58 | 4.72 | .42 | 4.66 | .47 | 4.53 | .83 | 4.71 | .39 |
| Task Avoid GO | 2.25 | .85 | 2.09 | .77 | 2.37 | .86 | 2.38 | .86 | 1.98 | .89 |
| PI Endogenous* | 4.22 | .79 | $4.57_{a}$ | .62 | $4.32_{b}$ | .70 | $3.60_{a\,b}$ | .78 | $4.66_{b}$ | .36 |
| PI Exogenous* | 1.95 | .83 | $1.80_{a}$ | .80 | $1.88_{b}$ | .81 | $2.34_{a\,b\,c}$ | .82 | $1.48_{c}$ | .51 |
| Growth Mindset | 4.46 | 1.00 | 4.65 | .94 | 4.33 | 1.06 | 4.45 | .95 | 4.37 | 1.04 |
| Fixed Mindset* | 2.50 | .99 | $2.22_{a}$ | .90 | $2.75_{a}$ | 1.10 | 2.55 | .87 | 2.42 | .97 |

*Significantly different across courses at $p < .05$. Means with the same subscript are significantly different at $p < .05$ in Tukey tests.

In contrast to the poor prediction for the CSCE155 courses, prediction for RAIK183H, the course for business-CS honors majors, was very high. The final regression model was significant ($R$ = .888, $R^2$ = .788, $F(7, 20) = 10.65$, $p < .0001$), Significant predictors were learning approach goal orientation (β = .579), performance approach goal orientation (β = -.256), performance avoid goal orientation (β = .288), task approach goal orientation (β = -.872), endogenous PI (β = .877), growth mindset (β = .769), and fixed mindset (β = .811). Differences in the entering motivation of these students predicted almost all of the difference in their final grade.

## 5.3 Prediction of Students' Course Withdrawal

Logistic regression was used to predict students' withdrawal from the course. Twenty-two students withdrew from the four courses combined so the only analysis that could be done was for the entire sample. Withdrawal was significantly predicted ($\chi^2$ (4) = 9.68, $p$ = .021). Likelihood of withdrawing was decreased by future time career connectedness (β = -.845, OR = .429) and learning approach goal orientation (β = -.635, OR = .530) and increased by having a growth mindset (β = .506, OR = 1.66).

# 6. DISCUSSION

## 6.1 Students' Entering Motivation

The findings suggest that students *are primarily choosing to take their CS1 course because they see it as personally relevant to their future goals*. Whether they chose them voluntarily or not, students expected their CS1 course to contribute to their personal growth and development and help them achieve their future academic and career goals. While this might be expected for those students who have chosen CS majors, this pattern of motivation was also present for the engineering majors in CSCE155N who are taking the class as a foundational course. The engineering majors were somewhat less motivated by personal relevance and goals (lower learning approach goal orientation and lower endogenous PI) and somewhat higher utility motivation (higher exogenous PI), but still were primarily motivated by personal growth.

Most emphasis on motivating students to take CS and STEM courses and major in CS or other STEM disciplines is focused on getting students to buy into the motivational pattern and goals that these students have when they start the course [1, 3., 7, 11, 17, 24]. While their positive motivation likely is somewhat due to their having already chosen a CS or other STEM major, as they would be predisposed to be motivated toward STEM classes once their major was chosen, it also is possible that these students chose a STEM major because they had developed this positive motivation toward STEM subjects.

## 6.2 Prediction of Students' Course Grades

Although the expectation would be that these students' very positive entering goals and motivation would be associated with high achievement in the class [1, 19, 24, 25, 28], students' grades were *not* predicted by their goal orientations and motivation in consistent or expected ways. The honors program students in the RAIK183H course fit expectations from prior research very well. Goal orientation and motivation highly predicted their course grades, with over 75% of the variance in grades explained. This is an exceptionally high level of predictability for educational classroom research. Apparently for honors students, who generally have developed strong academic strategic self-regulatory skills, achievement outcomes follow from their motivation.

But, they also had associations that were contrary to what are usually seen as positive motivators of achievement. Higher performance avoid and lower task approach goal orientations were associated with higher grades. These patterns are not generally considered productive as performance avoid goals are usually associated with lower achievement [23] and goals to do one's best are typically seen as promoting greater engagement and learning. It is not clear why these honors students would have these contrary associations. They are high achievers who are typically seen by others as "smart", so we speculate that, because they achieve highly, it is possible that fear of failing is a productive motivator for them because they believe they will succeed. They are in a competitive program and environment and may actually thrive in this environment in ways other more average students do not. The RAIK183H students did not have overly high fixed mindset relative to their growth mindset, but although usually seen as contrary, both were positively predictive of grades. Prior research has established that fixed mindsets are not necessarily detrimental as long as students are achieving at high levels [5]. Perhaps for these high achievers, a fixed mindset does not have the same negative consequences that it has for more average students.

Prediction of grades for the other 155 students was considerably poorer than that for the RAIK183H course. The best prediction was for CSCE155A where about 16% of grade variance was explained. Only about 8% of variance was explained for CSCE155E, and grades were not predicted significantly at all for CSCE155N. These findings indicate that course achievement was generally unassociated with entering motivation and goals for students in these classes. Students in the 155 classes are more diverse academically, relative to the RAIK183H honor students, which may lessen the impact of student motivation on their grades. Prior research also has shown that students in the CSCE155E and CSCE155N classes also adopt a more diverse range of motivated strategic self-regulatory profiles with more students adopting profiles that are dysfunctional for attaining high grades [19, 28]. Studies have shown that goal orientations and mindsets change across the semester in introductory CS courses [6, 9]. Because these and other motivational constructs are sensitive to within-class experiences, perhaps what happens in the 155 classes leads to more changes in students' goals and motivation than in RAIK183H, reducing the impacts of their entering motivation.

Also, it is not clear why CSCE155A predictability was so low. Other studies have shown that they adopt similar motivated strategic self-regulatory profiles to the RAIK183H students, so they are maintaining positive approaches to learning throughout the semester [19, 28]. But, their course grades are more distributed than the RAIK183H class, so they are not as uniformly achieving in ways consistent with their entering motivation and goal expectations. This perhaps makes them more susceptible to changes in motivation and goals as a result of during class experience which would reduce the prediction from their entering goals and beliefs.

For these courses, the only result that followed expected prediction was the positive association for learning approach goal orientation in the total student sample and for CSCE155E. These findings reinforce the importance of learning approach goal orientation discussed in [24]. Other beliefs had very contrary associations. Like RAIK183H, performance avoid goals were positively predictive of grades for all students and for CSCE155A. Also, both endogenous PI (all students, CSCE155A, and CSCE155E), reflecting instrumentality for personal future goals, and endogenous PI (all students and CSCE155A), reflecting utility-based instrumentality, were negatively associated with grades. This means that *students who saw the course as important for achieving future goals achieved less well*.

## 6.3 Prediction of Students' Course Withdrawal

Few students withdrew from these introductory CS1 courses. Only 22 students withdrew. Retention in the course was predicted by having high learning approach goal orientation and high future career connectedness. So those *students who were more strongly connected to their future career and who set goals to deeply learn the course material for their personal growth and development were less likely to drop out*. However, contrary to expectations, students who adopted a growth mindset were more likely to drop out. Because students with a growth mindset see their ability and intelligence as changing through learning, perhaps they drop out because they did not think that they were learning anything meaningful. It also may be that while these students want to learn the material, they do not believe that learning it is worth the effort required. Studies using interview data have shown that students in CSCE155N do not typically see the course as valuable [26]. The pattern of beliefs predictive of withdraw mirrored those found for grades, suggesting that grades and retention are associated with similar motivational patterns.

# 7. CONCLUSIONS

Findings support that students taking introductory CS1 courses are coming to the course with the goal orientation and motivation necessary for success. But, except for an honors course, these positive entering goals and motivation did not always predict course achievement and retention in the ways that would be anticipated from prior research and theory.

Results confirm the centrality of learning approach goal orientation for successful learning and achievement [24]. Essentially, students will not learn if they do not set goals to learn the material and they will not develop sophisticated knowledge and expertise if they do not set goals to learn the material deeply. Learning approach goals were the *only* consistent positive predictor of grades and retention. Findings along with those by [31] suggest that *getting CS1 students to set learning approach goals and supporting these goals with positive learning experiences is critical to successful achievement and to retaining students in classes*.

Results for perceived instrumentality in contrast were the opposite of what would be expected. Except for the honors students in RAIK183h where endogenous PI was positively associated with higher grades, endogenous and exogenous PI were negatively associated with grades. These anomalous results may be because perceiving the course as being highly instrumental to future success produces higher anxiety. This may cause CS1 students who are not having success to shift into more dysfunctional patterns of strategic self-regulation [19, 28] that lead to lower achievement. Certainly these findings suggest a need to more fully understand the dynamics of perceived instrumentality across the semester.

Results for mindsets were similarly confounding. As was found by [6], h*aving* a growth mindset was positively predictive of grades for the RAIK183H honors student, but was not predictive for other classes. However, having a growth mindset also was positively predictive of withdrawing from the course. Contrary to general theory of intelligence beliefs and prior research in CS classes [6], a fixed mindset was positively predictive of grades for RAIK183H and CSCE155A. Prior research suggests that a fixed mindset is not necessarily problematic if a student perceives that they have high ability and achieves at a high level [5]. So *a fixed mindset may to be positive for the generally high achieving students in these classes*. The similarity of findings here and [6] call for more study of mindsets in introductory CS classes.

Results are important for CS educators trying to understand how to motivate student achievement and retention in CS courses. Findings suggest that students are coming to introductory CS courses with the positive motivational dispositions necessary to succeed. This is true whether they are CS majors or non-majors. Except for highly selective honors students, however, these entering motivations are not necessarily motivating course achievement. When coupled with research showing that students entering goals and motivation shift over the semester in introductory CS courses [6, 9, 17], our findings suggest that the focus needs to be on within-course motivational and instructional strategies. What instructors do affects students' motivation. However, as noted by [15] addressing motivation in CS courses is complex and will require going beyond simple instructional and motivational strategies, as even specifically targeted motivational/affective efforts may produce only limited effects [17, 20].

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