# Achievement Goals in CS1: Replication and Extension

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## ABSTRACT

Replication research is rare in CS education. For this reason, it is often unclear to what extent our findings generalize beyond the context of their generation. The present paper is a replication and extension of Achievement Goal Theory research on CS1 students. Achievement goals are cognitive representations of desired competence (e.g., topic mastery, outperforming peers) in achievement settings, and can predict outcomes such as grades and interest. We study achievement goals and their effects on CS1 students at six institutions in four countries. Broad patterns are maintained — mastery goals are beneficial while appearance goals are not — but our data additionally admits fine-grained analyses that nuance these findings. In particular, students' motivations for goal pursuit can clarify relationships between performance goals and outcomes.

## CCS CONCEPTS

• **Social and professional topics → CS1**;

## KEYWORDS

CS1, novice programming, achievement goals, motivation, interest

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## 1 INTRODUCTION

What are the reasons that students take university courses? Some students seek topic mastery or personal improvement. Others seek to earn higher grades than their peers — some may strive for these grades for intrinsic reasons, while others seek to impress parents/teachers or earn rewards. **Achievement Goal Theory** (AGT) is a branch of educational psychology that studies goals and the effects of those goals in achievement settings. Students' achievement goals are related to a host of outcomes, including self-efficacy, interest, grades, and help-seeking [15].

Earlier studies have applied AGT to student outcomes in CS1 [17, 18], and we have learned much about student motivation from that work. That said, each of those studies takes place in CS1 courses at a single institution. We therefore have little evidence for the generalizability of those findings to other CS1 contexts. Recent, surprising results in CS education research [8, 9, 11, 16] attune us to the importance of conducting replication studies. The present paper begins the investigation into the replicability of what is known about the effects of student achievement goals in CS1. We report on data collected from six schools across four countries. We find what is theoretically expected at several schools, but find null results at other schools. We also extend prior CS education work to include students' reasons — autonomous or controlling — for the pursuit of grade-based goals. Finally, we include a discussion of some of the challenges inherent in large-scale replication work.

## 2 LITERATURE REVIEW

### 2.1 Importance of Replication

Few studies in CS education seek to replicate existing work [1]. Replication is important: it helps us determine whether a result generalizes outside of the context in which it was generated. Lack of replication studies complicates the creation of meta-analyses, inhibits theory-generation, and leads to distrust of published results [1]. Certainly, replication studies in CS often confirm expectations (for one example, see [12]). But here are two recent examples of what can be learned when such expectations are not met. Without these replications, our understanding of the given phenomena would be incomplete and incorrect.

**Effects of Subgoals.** A worked example consists of a problem statement and a step-by-step solution to the problem. Worked examples can be segmented into component pieces, and each piece can be augmented by a subgoal label: a brief descriptor for the function of that piece. For example, subgoals for solving a problem using a loop might include "initialize variables", "loop condition", and "update loop variable". Do subgoal labels help students learn? From the educational psychology literature, the answer is **yes**. From what we


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| Goal | Explanation |
|---|---|
| Mastery | Learn and master the course material |
| Performance-Appearance | Show others that one is smart and/or good at class-work |
| Performance-Normative | Perform better than other students |

**Table 1: Achievement Goals**

know so far in CS education research, the answer is **maybe**. For example, authors of one CS education study [9] taught students about while-loops using isomorphic or non-isomorphic example-practice pairs. When solving programming problems, and contrary to expectation, students in the isomorphic condition who were given subgoal labels performed more or as poorly as students who learned without subgoal labels. These authors also contrarily found that students who generate their own subgoal labels perform as poorly on a Parsons puzzle [10] as those who learned without subgoal labels [8].

**Predicting using Programming Behaviour.** Weak students can be identified through patterns of code compilations that exhibit unsuccessful attempts to fix a given error [16]. The Error Quotient (EQ) is a metric that is based on student compilation pairings, and positively and moderately correlates with student grades [16]. Except that sometimes it doesn't: in replication work, it was shown that the particular context (programming language, length of exercises) influences the predictive power of EQ [11].

## 2.2 Achievement Goals

AGT research suggests two particularly important types of achievement goals: mastery goals and performance goals. A summary of these achievement goals is given in Table 1 [18].

Students with mastery goals strive for personal improvement. There is little debate on the merits of mastery goals: throughout the three-decade-long AGT research trajectory, mastery goals have been posited and found to be adaptive (i.e. beneficial) in terms of a variety of positive outcomes (self-efficacy, interest, deep study strategies, etc.) [14, 15].

Appearance (striving to appear knowledgeable) and normative (striving to outperform peers) are two ways in which performance goals have been conceptualized. This is an important distinction, as appearance goals tend to correlate negatively with desirable outcomes, whereas normative goals tend to have null or positive correlations with such outcomes [6].

A surprise awaits in the educational psychology literature for anyone suspecting that mastery goals would positively correlate with course grades. In fact, normative goals, **not** mastery goals, show the most consistent correlation with psychology course grades: typically, normative goals positively correlate with course grades, and mastery goals are unrelated to course grades [14]. Prior work in CS education, however, has not replicated these findings: here, mastery goals positively correlate with course grades, and normative (and appearance) goals are null or negative predictors of course grades [17, 18]. The first aim of the present research, then, is to study these discordant results, answering the question: are the results in CS reliably different from those in psychology?

| Goal Complex | Explanation |
|---|---|
| Autonomous | Motivated by intrinsic reasons (e.g., enjoyment) |
| Controlling | Motivated by extrinsic reasons (e.g., rewards) |

**Table 2: Performance Goal Complexes**

Comparing the normative and appearance goals, we see that normative goals embody a success standard (outperforming peers), whereas appearance goals concern a consequence (or reason) for striving to achieve the goal. Recent work on **goal complexes** suggests that it is worthwhile to study other reasons, beyond appearance, for performance-goal pursuit. Broadly, there are two classes of reasons underlying the pursuit of performance goals (see Table 2): autonomous (enjoyment, challenge, career development, pride) and controlling (impressing others, gaining rewards) [15]. We expect from prior work [15] that performance goals pursued for autonomous reasons will positively relate to desirable educational outcomes, but that performance goals pursued for controlling reasons will be null or negative predictors of those outcomes. The second aim of this research is to use these two goal complexes to clarify and extend our understanding of performance goals.

# 3 METHOD

We sought participation in the study by posting in Summer 2016 to CS education email lists and a prominent CS education blog. Data was collected between September 2016 and May 2017. We report on data collected in CS1 courses at six research universities in four countries. CS1 is the first course taken by CS majors, but it is also often taken by non-majors for interest or as a requirement in their own discipline. As is common to many CS1 offerings, all courses included a mandatory lab component. Table 3 provides further contextual data from each institution.

## 3.1 Survey Administration

The study involved collecting data from students on two surveys: a pre-survey in the first two weeks of the course, and a post-survey in the last two weeks of the course prior to the exam.

**Goals Wave:** The pre-survey (see Appendix) contained our goal measures. These items (all seven-point, from "not at all" to "very") measure students' adoption of mastery, appearance, and normative goals. All items are taken from [18] and are based on earlier research in educational psychology. At four institutions, the pre-survey also contained our goal complexes items measuring student's autonomous and controlling reasons for performance goal pursuit. (Logistical issues prevented collection of goal complexes data at Institutions D and E.) Finally, we asked students to rate familiarity with five CS1 concepts and four code snippets on scales from 1 to 3. These nine items were averaged to form a prior experience index for each student.

**Interest Wave:** The post-survey contained 7-point items assessing students' interest in CS. Again, these items originate from the educational psychology literature [18].

**Grades:** Matching prior achievement goal literature, we use students' final exam grade as a measure of individual student performance.

| Institution | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| Country | USA | USA | USA | Canada | Finland | China |
| Class size | 260 | 436 | 388 | 352 | 280 | 207 |
| Exam-takers | 250 | 418 | 307 | 343 | 250 | 207 |
| Instruction language | English | English | English | English | Finnish | English |
| Coding language | Python | Java | Java | Python | Java | C |
| Number of weeks | 10 | 15 | 10 | 13 | 7 | 16 |
| Lecture style | live-coding | traditional & online text | Peer Instruction | Peer Instruction | live-coding & traditional | traditional |
| Required grade for major | 3.5 | B | 4.0 | N/A | N/A | N/A |

**Table 3: Contextual Data for Institutions A-F**

## 3.2 Data Analysis

Multiple linear regression was used to test the effects of goals on final exam grade and interest in CS. For each school, we report on a maximum of four models: two models that include mastery goals, appearance goals, normative goals, and all two-and three-way interactions; and two models that include autonomous and controlling goal complexes and their interaction. Continuous variables were centred but not standardized. Higher-order interactions were removed from models when nonsignificant. Gender was not a significant predictor in any model (on its own or interacting with other predictors) and so was excluded. Some models violated regression assumptions (constant variance, normal residuals), but transforming scores to address these assumptions did not change the interpretation of the models or coefficients. For ease of interpretation and comparison to prior work, untransformed scores are shown. In all tables, $^{***}$ represents $p < 0.001$, $^{**}$ represents $p < 0.01$, and $^{*}$ represents $p < 0.05$.

| | exam grade | | CS interest | |
|---|---|---|---|---|
| | goals | complexes | goals | complexes |
| (Intercept) | $83.21^{***}$ | $83.43^{***}$ | $5.46^{***}$ | $5.51^{***}$ |
| | (0.83) | (0.88) | (0.12) | (0.12) |
| mastery | $4.10^{***}$ | | $0.65^{***}$ | |
| | (0.92) | | (0.13) | |
| normative | 0.50 | | −0.02 | |
| | (0.72) | | (0.11) | |
| appearance | −0.20 | | 0.04 | |
| | (0.56) | | (0.08) | |
| prior_exp | $3.77^{**}$ | $4.86^{***}$ | 0.35 | 0.36 |
| | (1.33) | (1.36) | (0.18) | (0.19) |
| controlling | | −1.02 | | 0.02 |
| | | (0.66) | | (0.09) |
| autonomous | | $2.77^{**}$ | | $0.42^{**}$ |
| | | (0.92) | | (0.13) |
| $R^2$ | 0.27 | 0.16 | 0.30 | 0.19 |
| Adj. $R^2$ | 0.25 | 0.14 | 0.27 | 0.16 |
| Num. obs. | 120 | 123 | 102 | 105 |

**Table 4: Statistical Models, Institution A**

# 4 RESULTS

## 4.1 Institution A

Table 4 contains the coefficients, standard errors, and significance symbols for each of the four regression models at Institution A. As an example of interpreting this table, consider the mastery row. It shows that a one-point increase in mastery goals (e.g., from 4 out of 7 to 5 out of 7) is associated both with a 4.10 percentage-point increase in exam grade and a 0.65 point increase in interest. The stars affixed to each number show that these relationships are both statistically significant; the numbers in parentheses are standard errors. The Intercept row gives the mean exam grade and interest score for students at the midpoint of each of the goal predictors.

All four models are highly significant ($p < 0.0001$ in all cases). Data from Institution A replicates prior work in CS education. Specifically, mastery goals are positively associated with exam grade and course interest; and normative and appearance goals are not associated with exam grade nor with course interest. Agreeing with theoretical expectations, we find that normative goals pursued for autonomous reasons are positively associated with exam grade and course interest.

## 4.2 Institution B

Table 5 contains the four models for Institution B. The grades models are significant ($p < 0.05$), and the interest models are also significant ($p = 0$). As expected, mastery goals positively and significantly

| | exam grade | | CS interest | |
|---|---|---|---|---|
| | goals | complexes | goals | complexes |
| (Intercept) | $69.00^{***}$ | $71.23^{***}$ | $4.78^{***}$ | $4.79^{***}$ |
| | (2.07) | (1.98) | (0.10) | (0.10) |
| mastery | $4.99^{*}$ | | $0.64^{***}$ | |
| | (2.13) | | (0.10) | |
| normative | 2.57 | | −0.07 | |
| | (2.09) | | (0.09) | |
| appearance | −2.55 | | −0.01 | |
| | (1.33) | | (0.06) | |
| prior_exp | 4.83 | $6.74^{*}$ | $0.72^{***}$ | $0.78^{***}$ |
| | (2.96) | (3.01) | (0.15) | (0.15) |
| norm:appear | $2.95^{*}$ | | | |
| | (1.17) | | | |
| controlling | | −2.18 | | −0.02 |
| | | (1.38) | | (0.07) |
| autonomous | | 4.12 | | $0.45^{***}$ |
| | | (2.44) | | (0.12) |
| $R^2$ | 0.10 | 0.04 | 0.26 | 0.18 |
| Adj. $R^2$ | 0.07 | 0.02 | 0.24 | 0.17 |
| Num. obs. | 199 | 198 | 199 | 198 |

**Table 5: Statistical Models, Institution B. "norm:appear" is the interaction between normative and appearance goals.**

| | exam grade | | CS interest | |
|---|---|---|---|---|
| | goals | complexes | goals | complexes |
| (Intercept) | 84.60*** | 84.47*** | 5.36*** | 5.37*** |
| | (1.38) | (1.40) | (0.08) | (0.09) |
| mastery | −0.07 | | 0.56*** | |
| | (1.88) | | (0.12) | |
| normative | 1.05 | | −0.05 | |
| | (1.27) | | (0.08) | |
| appearance | 1.23 | | 0.03 | |
| | (0.93) | | (0.05) | |
| prior_exp | 2.86 | 2.99 | 0.39** | 0.36** |
| | (2.16) | (2.21) | (0.13) | (0.14) |
| controlling | | 1.02 | | −0.07 |
| | | (0.93) | | (0.06) |
| autonomous | | −1.04 | | 0.45*** |
| | | (1.78) | | (0.11) |
| $R^2$ | 0.04 | 0.02 | 0.15 | 0.11 |
| Adj. $R^2$ | 0.02 | 0.00 | 0.13 | 0.10 |
| Num. obs. | 178 | 176 | 225 | 224 |

**Table 6: Statistical Models, Institution C**

predict exam grades and interest. The interaction (norm:appear) in the first exam grades model is an oddity, however. This interaction shows that students low on normative goals and low on appearance goals perform well on the exam (expected), but that students high on both goals perform almost as well (unexpected). In terms of goal complexes, we find a (nonsignificant, $p < 0.1$) trend that autonomous motives and grades are positively correlated, and a significant positive correlation between autonomous motives and interest.

In sum, effects for Institution B are weaker than those for Institution A, but the overall pattern of results is sustained.

### 4.3 Institution C

Table 6 contains the four models for Institution C. For the first time, we have an institution where some expected findings do **not** replicate. In particular, the grades models are nonsignificant ($p = 0.15$ and $p = 0.37$, respectively). No predictors, not even prior experience, are significant here. By contrast, the interest models are highly significant ($p = 0$) and, as expected, mastery goals and autonomous motives positively correlate with interest in CS.

### 4.4 Institution D

Table 7 contains the two models for Institution D. Data from Institution D somewhat mirrors that of Institution C. The grades model is significant ($p = 0.003$), but the only significant predictor is students' prior experience. The interest model is highly significant ($p = 0$), and, as expected, mastery goals positively correlate with interest in CS.

### 4.5 Institution E

Table 8 contains the two models for Institution E. The grades model is significant ($p = 0.007$). In addition to prior experience, the only significant predictor is normative goals and, contrary to expectations, these goals **positively** correlated with exam grade. We note, however, that the p-value is very close to the significance threshold.

| | exam grade | CS interest |
|---|---|---|
| | goals | goals |
| (Intercept) | 74.27*** | 5.73*** |
| | (1.14) | (0.08) |
| mastery | 1.51 | 0.39*** |
| | (1.23) | (0.09) |
| normative | 0.36 | 0.04 |
| | (0.79) | (0.06) |
| appearance | −0.69 | −0.01 |
| | (0.99) | (0.07) |
| prior_exp | 7.11*** | 0.42** |
| | (1.99) | (0.13) |
| $R^2$ | 0.07 | 0.20 |
| Adj. $R^2$ | 0.06 | 0.18 |
| Num. obs. | 219 | 162 |

**Table 7: Statistical Models, Institution D**

| | exam grade | CS interest |
|---|---|---|
| | goals | goals |
| (Intercept) | 90.81*** | 5.92*** |
| | (0.60) | (0.09) |
| mastery | −0.70 | 0.42*** |
| | (0.66) | (0.10) |
| normative | 0.84* | 0.01 |
| | (0.42) | (0.06) |
| appearance | 0.38 | 0.06 |
| | (0.90) | (0.15) |
| prior_exp | 2.63** | 0.21 |
| | (1.00) | (0.15) |
| $R^2$ | 0.06 | 0.19 |
| Adj. $R^2$ | 0.05 | 0.16 |
| Num. obs. | 214 | 119 |

**Table 8: Statistical Models, Institution E**

Still, this does remain as the only institution in this and prior CS education studies where normative goals have shown to be beneficial in any way. The interest model aligns more closely to expectations: the model is significant ($p = 0$), and mastery goals positively predict interest in CS.

### 4.6 Institution F

The pattern of results for our final institution (Table 9) is similar to those for Institutions C and D. The grades models are both nonsignificant ($p > 0.5$), with no predictor meeting significance. The interest models are both significant ($p = 0.006$ and $p = 0.001$, respectively), matching hypotheses, mastery goals and autonomous motives positively relate to interest in CS.

## 5 DISCUSSION

### 5.1 Achievement Goals

What have we learned about achievement goals in CS1 from this replication study? First, we confirm from prior studies that appearance goals are **not** adaptive in CS1 courses. An odd interaction at Institution B is subdued by much stronger evidence suggesting that these goals are not related to grades and interest. Given the defensive and stereotyped climates associated with CS courses [3, 7],

| | exam grade | | CS interest | |
|---|---|---|---|---|
| | **goals** | **complexes** | **goals** | **complexes** |
| (Intercept) | $66.01^{***}$ | $65.22^{***}$ | $5.58^{***}$ | $5.60^{***}$ |
| | (2.63) | (2.75) | (0.16) | (0.15) |
| mastery | 1.57 | | $0.50^{*}$ | |
| | (3.04) | | (0.22) | |
| normative | 2.75 | | 0.20 | |
| | (2.44) | | (0.17) | |
| appearance | −0.36 | | 0.06 | |
| | (1.63) | | (0.10) | |
| prior_exp | 4.62 | 2.24 | 0.45 | 0.19 |
| | (5.78) | (6.16) | (0.32) | (0.33) |
| controlling | | −0.62 | | 0.02 |
| | | (1.71) | | (0.09) |
| autonomous | | −0.09 | | $0.76^{**}$ |
| | | (3.59) | | (0.21) |
| $R^2$ | 0.06 | 0.01 | 0.34 | 0.38 |
| Adj. $R^2$ | -0.01 | -0.05 | 0.26 | 0.32 |
| Num. obs. | 59 | 58 | 39 | 38 |

**Table 9: Statistical Models, Institution F**

| Institution | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| Grades | ✓ | ✓ | ✗ | ✗ | ✗ | ✗ |
| Interest | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

**Table 10: Does each institution's results replicate previous results in CS on Mastery goals? ✓indicates full support, ✗ indicates no support.**

where students have been known to brag and show-off their knowledge, we are particularly heartened to find no link between public demonstrations of knowledge and valued course outcomes.

Second, we have more evidence for the benefits of mastery goals. Mastery goals positively relate to interest at all six institutions, and positively relate to exam grades at two institutions; see Table 10. We see no negative effects of mastery goals anywhere in our data. As in prior research [18], our data suggests that a focus on mastery goals is an optimal motivation pattern for CS1 students.

Third, we broadly replicate the finding that normative goals do not correlate with interest and grades in CS1 [17, 18]. Recalling from the educational psychology literature that normative goals typically positively correlate with exam grades, we are now more confident than before that CS is different in this regard.

Finally, we have conducted the first known study of goal complexes in the CS education literature. Our results strengthen and complement what we know about normative goal pursuit in CS1. Students who seek normative success for autonomous reasons do so for the challenge and enjoyment associated with learning CS, or to attain valued career opportunities. We find benefits of these autonomous goal strivings. Students who seek normative success for controlling reasons are instead motivated by others' opinions or rewards. We find **no** benefits of these controlling strivings.

We therefore conclude, at least at our institutions, that those students motivated to learn the subject (mastery goal) or autonomously attain high grades (autonomous performance goal complex) are often the students that perform well in CS1 and become interested in CS.

## 5.2 Future Work

Many CS departments, including some in this work, are currently facing enrollment pressure through elevated student numbers [13]. This, in turn, leads to increased requirements and competition among students seeking to enter a CS program. We wonder to what extent this competitive climate influences students' motivational patterns and the processes that stem from these motivations. In particular, is there a new performance goal complex borne from students' desire to get accepted into a CS program? It is unclear whether such a goal complex would be autonomous or controlling in nature, or whether this determination contextually depends on students' reasons for studying CS. We are not aware of relevant AGT work on this question; it remains as a potentially "missing" but important goal complex in the present work. In addition, we wonder to what extent our results would replicate in small colleges, where class sizes tend to be smaller and where instructor-student interactions can therefore be more frequent.

## 5.3 Challenges of Replication Research

We note three challenges particular to survey-based multi-institution replication research. First, we hoped to use a centrally-administered survey to collect data at all institutions. However, to meet institutional requirements or reduce survey fatigue in the presence of multiple research projects, some researchers chose to administer their own local survey. This complicated data collation and required additional effort from researchers. Second, not all institutions will use the same language of instruction; our researcher at Institution E translated the surveys, but a more formalized process would likely be useful and reduce burden incurred by translation. Third, course start and end dates will vary between institutions from several days to several months. This requires a "rolling" data-collection period, where surveys are started and stopped based on participating institution schedules. Clear data-management, administration, and communication are key here.

# 6 CONCLUSION

In this replication and extension study, we have conducted achievement goal research in CS1 courses at six institutions. We find further evidence that mastery goals are adaptive for CS1 students in terms of grades and interest in CS. In addition, we now understand that the pattern surrounding normative performance goals is more complex than previously thought. Specifically, CS1 students **can** become interested in CS when striving for normative goals; what ultimately matters here is their motivation complex (autonomous or controlling). We echo a conclusion offered by Gaudreau [4] from the educational psychology literature: as educators, we can do well by promoting the autonomous achievement of goals to our students. While it is unlikely that we can influence students away from normative goals, we may be able to help students make explicit their reasons undergirding those goals. Our study suggests that encouraging autonomous reasons for goal pursuit may strengthen interest in CS; direct tests of this hypothesis are warranted.

Replication research has enhanced our understanding of achievement goals in CS. We urge other CS education researchers to put their hypotheses to the test and engage the community in replication work.

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## A MASTERY AND PERFORMANCE

These questions make up the mastery- and performance-goal scales on the pre-survey.

Indicate the extent to which each statement is true of you from 1 (not at all) to 7 (very):

Mastery [2]:

- My aim is to completely master the material presented in this class.
- I am striving to understand the content of this course as thoroughly as possible.
- My goal is to learn as much as possible.

Performance, appearance [18]:

- One of my goals is to have other students in my class think I am good at my class work.
- One of my goals is to show others that I'm good at my class work.
- One of my goals is to show others that class work is easy for me.
- One of my goals is to look smart in comparison to other students in my class.
- I aim to look smart compared to others in my class.

Performance, normative [2]:

- My aim is to perform well relative to other students.
- I am striving to do well compared to other students.
- My goal is to perform better than the other students.

## B GOAL COMPLEXES

These questions make up the autonomous and controlling scales on the pre-survey.

Here is a possible goal that you might have for your Computer Science course: "I am striving to do well compared to other students." Assume you agreed, even if only a little bit, with that goal. What reason(s) motivate you to pursue this goal in your class? [15]

Please choose the appropriate response for each item from 1 (not at all) to 7 (very) [items presented in random order]: Autonomous

- Pursuing this goal is fun and enjoyable.
- Pursuing this goal provides challenge.
- Attaining this goal is important to my personal or career development.
- Attaining this goal would make me feel proud.
- I'll feel good if I attain this goal.

Controlling

- Attaining this goal would impress others whose opinions I value, such as peers, teachers, or parents.
- Attaining this goal would bring rewards from others, such as friends, teachers, or parents.

## C INTEREST

These questions make up the interest scale on the post-survey.

Indicate the extent to which each statement is true of you from 1 (not at all) to 7 (very) [5]:

- I think what we are learning in this class is interesting.
- I think I will be able to use what I learn in this course in other courses.
- I would recommend this class to others.
- I am enjoying this computer science class very much.
- I think the field of computer science is very interesting.
- This class has been a waste of my time.
- I'm glad I took this class.
- I think the course material in this class is useful for me to learn.
- I would like to take more computer science classes after this one.
- I am more likely to register for another computer science class because of my experience in this course.