A STUDY OF NON-COMPUTING MAJORS' GROWTH MINDSET, SELF-EFFICACY AND PERCEIVED CS RELEVANCE IN CS1

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ABSTRACT

A Study of Non-computing Majors' Growth Mindset, Self-efficacy and Perceived CS Relevance in CS1

Jae Hyuk Yoo

As the demand for programming skills in today's job market is rapidly increasing for disciplines outside of computing, CS courses have experienced spikes in enrollment for non-majors. Students in disciplines including art, design and biological sciences are now often required to take introductory CS courses. Previous research has shown the role of growth mindset, self-efficacy and relevance in student success within CS but such metrics are largely unknown for non-majors. In this thesis, we surveyed non-majors in CS1 at Cal Poly, San Luis Obispo during the early and late weeks of the quarter to gain insights on their growth mindset, their self-efficacy and the perceived relevance of the course to their lives. In our analysis, we discovered that non-majors' levels of growth mindset and of self-efficacy decreased throughout the duration of CS1 with additional differences by gender. However, non-majors largely found that the material covered in CS1 was highly relevant to their academic and professional careers despite being challenged by it. These findings provide important insights into the experiences of non-majors learning to code and can help better serve a more diverse population of students.

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Chapter 1

INTRODUCTION

The demand for programming skills in today's job market is rapidly increasing for disciplines outside of Computer Science (CS) and even outside of STEM in general [28, 29]. In fact, some have predicted that "end-user programmers" in other disciplines outnumber professional programmers by almost 20 times [16]. These disciplines may include but are certainly not limited to Art, Design, Entertainment and even Medicine. Many universities now offer and some even require non-computing majors (whom we refer to as "non-majors" in this study) to take introductory CS courses in order to learn the skills that make up the foundations of CS and programming. Consequently, CS courses have seen massive spikes in enrollment for both majors and non-majors alike with up to 177% increase in non-major enrollment in intro-level courses among a sample of 51 universities [4].

While these numbers are certainly encouraging and suggest a trend of major growth in the field, the computing field has had a long-standing struggle with diversity and retention which has yet to be solved [25]. Many students who leave the major leave due to a lack of a sense of belonging, grades, or difficulty and characterize CS as being anti-social and boring [3]. Additionally, many new students have perceptions of CS as being "only for smart people," which suggests a fixed mindset in learning CS [30, 34]. Previous research also suggests that students' performance and overall motivation to learn is highly influenced by their self-efficacy [19, 24], sometimes with differing effects in men versus women.

To combat the issue of retention among computing students at Cal Poly, San Luis Obispo, offerings of CS0 were designed and introduced to ease students with no prior experience in programming into computing [32]. The addition of the course led to broad success with significant increases in graduation rates as well as overall increases in self-efficacy and attitudes towards CS among students. However, the experience has not been the same for non-majors taking introductory CS courses. Some of these differing experiences were apparent in a 3 year observation of a new cross-disciplinary minor called Computing for the Interactive Arts (CIA) at Cal Poly [33]. Art students in the minor often felt that the knowledge gap of taking CS courses was a major hurdle in pursuing the minor while for CS students, taking art courses could be considered a "break" from their normal CS curriculum. Similar sentiments have been voiced by students majoring in Graphic Communications (GRC) concentrating in UI/UX who are also required to take the Computational Art focus of CS0 as well as CS1. CS1 has the highest D-grade/Fail/Withdraw (DFW) rate among GRC majors at 38% [27].

A number of recommendations have been made by organizations such as the Association for Computing Machinery (ACM) and researchers such as Allan Fisher and Jane Margolis [25, 8] to help battle these issues. Such recommendations include gathering information about student progressions through courses and programs at a granular level as well as taking into account differences in prior experience and motivation when administering CS courses, particularly to diverse groups of students. Although many of these recommendations have been put in action, little formal data has been collected to discover trends among non-majors in CS courses and how they compare to majors in the same courses, particularly with regards to growth mindset and self-efficacy.

In this research we assess the growth mindset, self-efficacy and perceived course relevance to non-majors in CS1 at Cal Poly, San Luis Obispo. By conducting surveys during the beginning of the course as well as the end of the course, we observe students' levels of growth mindset, self-efficacy and perceived course relevance and how they change throughout the course. Our findings suggest that students experienced some changes in growth mindset and self-efficacy throughout the duration of the course with some differences in gender. However, students still found CS1 to be highly relevant to their lives.

The paper proceeds as follows: we begin by reviewing existing literature and related works on growth mindset, self-efficacy and relevance to establish definitions and understanding of the concepts, particularly in the context of CS (Chapter 2). Then, we define our research questions and methods for gathering the data (Chapter 3) before presenting our findings and analysis of the data (Chapter 4). Finally, we discuss our findings and their implications (Chapter 5) as well as threats to validity and future works (Chapter 6).

Chapter 2

BACKGROUND

The three metrics through which we examine the experiences of non-majors in introductory CS courses are growth mindset, self-efficacy and relevance. Growth mindset and self-efficacy are both concepts that have been extensively studied in the context of CS education and education in general. Therefore, it is important to define these terms by discussing their foundations as well as how they have been studied by CS education researchers in the past. Relevance on the other hand has yet to be defined as a scientific construct in the same way that growth mindset and self-efficacy have. Nevertheless, we find it important to discuss some of the ways it has been used and measured in the context of both CS education and education at large to support our study.

2.1 Growth Mindset

Growth mindset is a term that was coined and introduced by psychologist Carol Dweck [7]. Dweck states that there are two mindsets: fixed mindset and growth mindset, towards which a person can skew. A student with a fixed mindset measures success based on their ability to be correct and mistake-free. They lean towards the belief that one has a fixed amount of intelligence or talent which cannot be changed. A student with a growth mindset measures success based on incremental growth and improvement. They lean towards the belief that intelligence and talent are malleable and can be significantly improved with effort. The original Dweck Mindset Instrument (DMI) consists of the following three questions answered on a Likert scale [6].

1. You have a certain amount of intelligence, and you can't really do much to change it.
2. Your intelligence is something about you that you can't change very much.
3. You can learn new things, but you can't really change your basic intelligence.

Previous works have shown significant decreases in growth mindset and increases in fixed mindset in students after introductory CS courses [21, 9]. Therefore, we find it important to investigate if similar trends exists for non-majors in introductory CS at Cal Poly.

It has been widely accepted in education that a growth mindset is positively related to students' achievement [5]. However, extensive research has not been done to suggest significant effects of growth or fixed mindsets in CS. Interventions have been less effective in CS and Kaijanaho and Tirronen have even concluded in their study that the relationship between CS students' mindsets and their course outcome was statistically non-significant [14].

Nevertheless, CS Education researchers have encouraged a shift towards a growth mindset-centered way of teaching. Murphy and Thomas have outlined some notable implications of this shift [23]. They suggest that because much of mindset theories have to do with the way in which an individual responds to challenges, a correlation between the way CS students respond to the challenges of learning programming and their intelligence mindset can be grounds for interventions to encourage a growth mindset. Additionally, examining the differences in mindsets between genders may provide further insights into the gender gap in CS.

To investigate the way mindsets impact student success, Gorson and O'Rourke have conducted interviews among undergraduate students in CS1.5 – a course designed to prepare students to move on to CS2 if they felt less prepared to do so [11]. In the study, participants were given mindset surveys and were interviewed on their thoughts about their programming experiences as well as general thoughts on programming intelligence. Results from the study showed that out of nine students interviewed, only one student's thoughts on mindset which was coded as Growth aligned with their thoughts on behavior which was coded as Growth. The rest of the participants were either misaligned in their thoughts or showed a mixed mindset. This suggests that students may benefit from being exposed to mindset theories to help better solidify what they believe about intelligence and learning in CS.

2.2 Self-Efficacy

Self-efficacy is defined as one's belief in their ability to achieve a certain outcome. This idea was originally presented in Albert Bandura's social cognitive theory. Bandura's theory says that the strength of one's self-efficacy to achieve a certain outcome heavily influences the behavior the individual displays in order to reach success [2]. Bandura's theory also states that this behavior, which is influenced by one's self-efficacy, and the expectation of eventual success heavily determine the persistence exerted by an individual to reach success.

This relationship between self-efficacy and student performance in the context of introductory CS has also been studied by Lishinski et al. [19]. To examine the relationship between certain self-regulated learning (SRL) constructs and student outcomes in CS1, a survey was sent out to 346 students at a large university. The survey used subscales for four different components of SRL: self-efficacy, metacognitive strategies, intrinsic goal orientation and extrinsic goal orientation. These subscales were adapted from the Motivated Strategies for Learning Questionnaire (MSLQ), a tool that is widely accepted to measure students' motivation and learning strategies [24]. Students were assessed for the self-efficacy subscale three different times in order to find their self-efficacy-performance correlation based on projects and exams.

In their analysis, Lishinski et al. found that self-efficacy was the most important predictor of student performance in CS1. Notably, women experienced a significantly sharper change in self-efficacy-performance correlation between the initial and first repeated measure and no significant change between the first and second repeated measure. Men on the other hand had significant changes in both intervals. These findings suggest that women's self-efficacy is significantly more malleable early on in a course. Alternatively, women may have a more accurate assessment of their ability than men. The study also revealed a feedback loop in which students' metacognitive strategies and goals influence their self-efficacy which impacts their performance which further impacts their self-efficacy and so on. Because self-efficacy and confidence can play such significant roles in affecting both men and women's performance and vice-versa, we must examine the role it plays in non-majors' experiences in intro CS as well as how it changes throughout the course.

Gorson and O'Rourke have also investigated the ways in which students assess their own abilities [11]. Among the top criteria for such assessments were "better if you do it yourself (without help)", "speed", and "memorizing syntax". They found that students who were just starting out in CS were likely to use such criteria to frequently perform self-efficacy appraisals based on their performance on assignments and assessments. This study reveals an anomaly in mindset theory in the context of CS. It is clear that students' mindsets and self-efficacy interact in a way that affects their persistence and motivation. However, it is unclear how students' self-perceived beliefs about their abilities correlate with their actual performance in CS.

2.3 Relevance

As explained by Stuckey et al., the term relevance in the context of Science Education has not been clearly defined yet has been used in a variety of ways [26]. In our research we define relevance as the level to which a student finds the course to be applicable to their major, interests, career goals, etc. Students are often concerned about whether the materials being taught in a certain course will apply to them in the future and are left to wonder,"What's in it for me?" [10]. Previous research suggests that relevance is one of the key factors to a student's motivation to engage with the material being taught [10, 15]. Motivation scientists have led efforts to develop interventions that help students draw relevance in what they are learning in school to their lives [1]. However, these efforts within the education and psychological sciences have come with difficulties in defining what it means for schooling – primary, secondary and higher education – to be relevant to students' lives.

One notable example of the impact of relevance in CS education is the Media Computation course at Georgia Tech. Since 1999, educators at Georgia Tech have required all students to take introductory programming courses as a way to prepare them for a world that is increasingly dependent on technology [12]. Initially, a one-course-for-all approach was taken in which faculty saw a 78% average pass rate through a 4-year period. Although 78% seemed to be a reasonable number of students passing an introductory CS course, they observed that pass rates for students in certain disciplines had fallen below 50%. As a response, a Media Computation course was developed by Mark Guzdial to provide a more contextual education experience for non-CS majors. One of the focuses of this new course was relevance of the content in everyday life such as performing features of applications like Photoshop using code. As a result, pass rates consistently stayed over 85% over the course of 10 years. Students' outlook of CS was also increasingly positive with some students even expressing the course's relevance to their interests and goals. This success suggests that contextual CS education works for non-majors.

Similar changes have also been made at Cal Poly with success in the previously mentioned CS0 course [32]. However, this study focuses on CS majors and it is possible that expectations for a CS course for a computing major may widely differ from those of a non-major. For example, if an introductory CS course merely teaches programming or coding by itself without establishing a connection to real-life applications, a computing student may be more likely to find value in it than a GRC student, thus impacting their engagement and performance in the course.

Chapter 3

STUDY DESIGN

3.1 Study Context

In this study, we examined the experiences of non-majors (students majoring in non-computing disciplines) enrolled in CS1 at Cal Poly, San Luis Obispo, a public polytechnic university in the United States. These non-majors represented the following colleges which exist at Cal Poly: College of Science and Math(COSAM), College of Engineering(CENG), Orfalea College of Business(OCOB), College of Liberal Arts(CLA) and College of Agriculture, Food and Environmental Sciences(CAFES). The non-computing majors within CENG represented in this study are Biomedical Engineering, Civil Engineering, Electrical Engineering, General Engineering, Industrial Engineering, Manufacturing Engineering and Mechanical Engineering. It should be noted that with white students making up 54% of the student body, Cal Poly is not representative of most public universities in the state of California.

Students in this course learn the fundamentals of CS (e.g., control structures, data types, and input/output) as well as the syntax and semantics of the Python programming language. The course consists of labs, programming assignments as well as written exams. The course was held in an online environment due to COVID-19. However, this study does not focus the effects of an online learning environment.

3.2 Research Questions

In this study, we address the following research questions

RQ1. What are non-computing majors' Growth Mindset levels while taking CS1? How do these levels change throughout the course? Common perceptions of CS include characterizations of CS as being only for "smart people," attributing performance to a fixed level of intelligence one is born with. Prior work has tended to focus on CS majors taking these courses. In our research, we examine whether non-majors experience similar feelings when taking CS1 by measuring their level of growth mindset and how it changes throughout the course.

RQ2. What are non-computing majors' levels of computing self-efficacy while taking CS1? How do these levels change throughout the course? There is a strong correlation between self-efficacy and student performance in CS1. Researchers have also seen feedback loops in which each continue to affect the other. In our research we examine the self-efficacy of non-majors and how it changes throughout the course.

RQ3. To what extent do non-computing majors find CS1 relevant to their discipline, career, etc.? How does this change throughout the course? Research has shown that students are more likely to engage in course material if they establish some sort of relevance of the material to their lives. Because CS1 is the fundamental course for computing, computing majors may have an easier time finding relevance in the materials covered in the course as well as how it will help them in future courses. Therefore, we examine the perceived relevance of CS1 for non-majors, to whom the course may merely be a graduation requirement. We also examine the change in perceived relevance throughout the course.

3.3 Survey

In order to examine the metrics above, a Google Forms survey was distributed to four sections of CS1 (called CPE/CSC 101) at Cal Poly, San Luis Obispo during the Spring 2021 quarter. The full test of the survey can be found in the Appendix. Because most CS majors take CS1 during Fall or Winter quarters, Spring sections of CS1 consist mostly of non-majors who are required to take the course to fulfill a graduation requirement. A breakdown of the disciplines represented will be provided in Chapter 4.

Upon approval of the Cal Poly Institutional Review Board(IRB), surveys were given to instructors of the sections who distributed them to students. Although the surveys were not required, they were conducted during class time to increase chances of participation. To observe changes in students' answers from the beginning of the course to the end of the course, the survey was conducted early in the quarter and a repeated measure was taken later in the quarter. Informed consent was obtained by each student prior to their completion of the survey.

3.3.1 Growth Mindset

To measure students' growth mindset levels, the survey asked four questions about an individual's mindset when learning computing. Questions were adapted from the original Dweck Mindset Instrument (DMI) [7], answered on a 5-point Likert scale (Strongly Agree 1 - 5 Strongly Disagree). Two questions were positively worded, then reverse coded and two questions were negatively worded. These questions are meant to gain an insight into how malleable a student thinks their knowledge or understanding of computing is. These questions are shown in Table 3.1. Each student

Table 3.1: Survey items for growth mindset

	Growth Mindset Questions
1	You have a certain amount of computing ability, and you can't do much to change it.
2	No matter who you are, you can significantly change your computing ability.
3	You can learn new things but you can't really change your level of computing ability.
4	No matter what level of computing ability you have, you can always change it quite a bit.

Table 3.2: Survey items for self-efficacy

	Self-efficacy Questions
1	I believe I will receive an excellent grade in this class.
2	I'm certain I can understand the most difficult material presented in the readings for this course.
3	I'm confident I can do an excellent job on the assignments and tests in this course.
4	I'm certain I can master the skills being taught in this class.

was then given a growth mindset score on a 1-5 scale using the average of the values of these questions. Scores were not necessarily integers but were values between 1 and 5 (inclusive) in increments of .25.

3.3.2 Self-Efficacy

To measure students' self-efficacy levels, the survey asked four questions about how students believe they will perform and master the skills taught in the course. Questions were adapted from a subset of questions included in the MSLQ [24], also answered on the same 5-point Likert scale as the previous metric. All four questions in this section were positively worded. These questions are shown in Table 3.2.

Table 3.3: Survey items for relevance

	Relevance Questions
1	CSC 101 is relevant to my general interests.
2	CSC 101 is relevant to my interests that are related to my major.
3	Taking CSC 101 makes me want to learn more about programming in general.
4	CSC 101 has taught me many skills that I will likely use in future courses or jobs.

3.3.3 Relevance

To measure the relevance of CS1, the survey asked four questions about the level to which students perceive CS1 to be relevant in their lives. These questions were also answered on the same 5-point Likert scale as the previous metrics. They were formulated while keeping in mind students' career goals, interest in computing, and interests as they pertain to their major as well as life outside of school. All four questions in this section were positively worded. These questions are shown in Table 3.3.

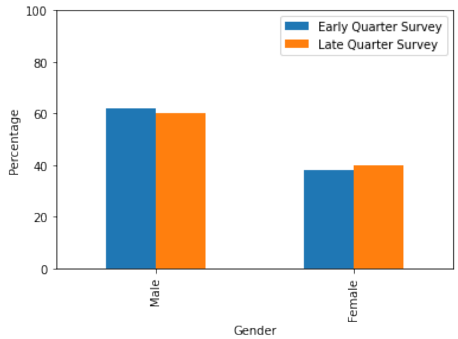
Additionally for this section, students were asked an optional free response question to elaborate on their answers to the four questions. An analysis of students' answers will also be presented.

Chapter 4

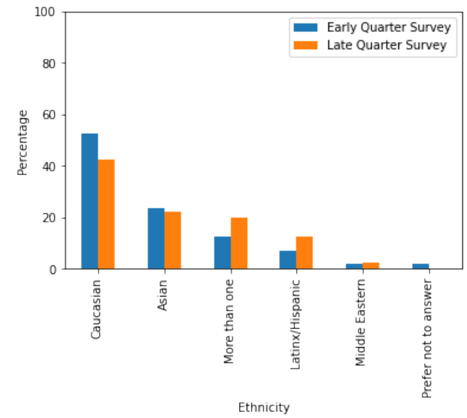
ANALYSIS

To collect data for this study, the survey described in Chapter 3 was distributed to CS1 students at Cal Poly, San Luis Obispo during the Spring 2021 offerings of the course. The survey was conducted twice—during weeks 2 and 8 of the 10-week quarter—to observe changes in students' responses after having almost completed the course. By Week 2, students had been assigned two labs, their first project and had taken their first quiz. By Week 8, students had been assigned their seventh lab, fourth project, and had taken eight quizzes in addition to a midterm exam or cumulative quiz.

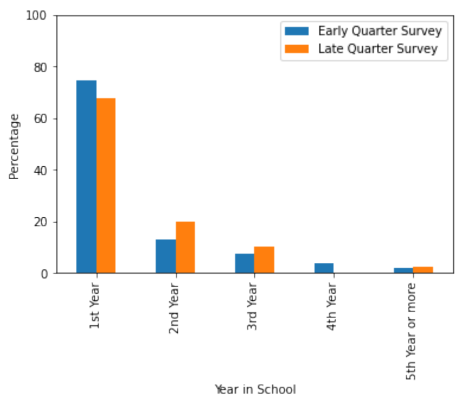
Because we consider the sample of students who responded to both surveys to be small, our analysis will be two-fold: between-subjects and within-subjects. Excluding the computing majors who responded to the surveys (2 in early-quarter and 2 in late-quarter), 55 students responded to the early-quarter survey, 40 students responded to the late-quarter survey and a total of 22 students responded to both surveys. Figure 4.1 shows the percentages of demographic subgroups in the early-quarter survey and the late-quarter survey. Our between-subjects analysis will be done by examining the responses of students who only responded to the early-quarter survey and comparing them with the responses of all students who responded to the late-quarter survey. Then, in our within-subjects analysis we will examine responses from students who responded to both surveys. The within-subjects analysis will help us avoid observing effects that are purely a result of inherent differences between individual students.



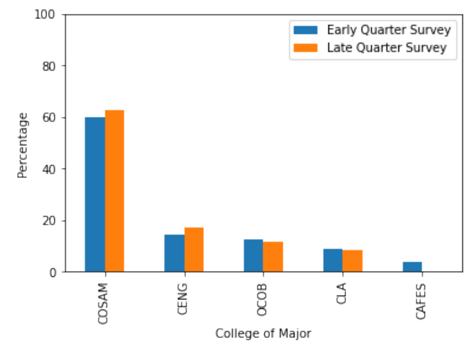
(a) Gender by percentage



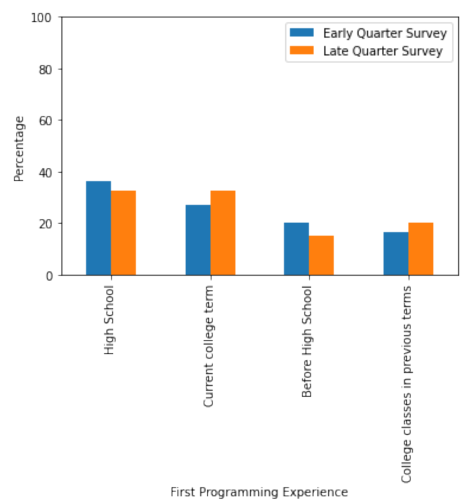
(b) Ethnicity by percentage



(c) Year in school by percentage



(d) College of major by percentage



(e) First programming experience by percentage

Figure 4.1: Percentages of demographic groups represented in the early-quarter versus late-quarter surveys

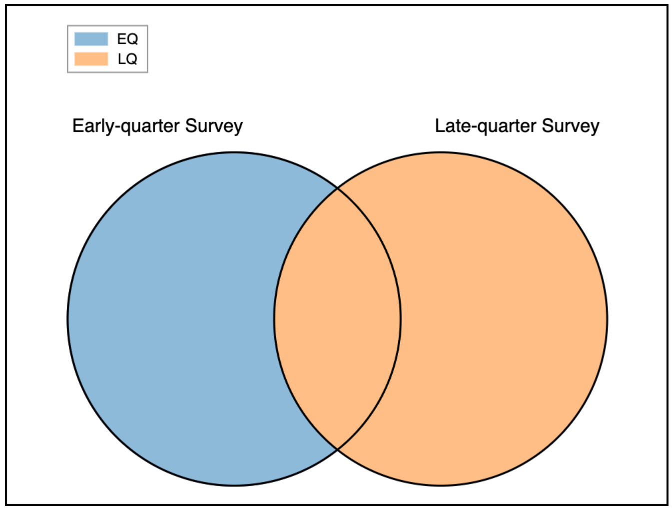


Figure 4.2: Breakdown of samples EQ and LQ

4.1 Between-subjects Analysis

To compare the responses of students who only responded to the early-quarter survey (EQ) to the responses of all students who responded to the late-quarter survey (LQ), the responses of those who responded to both surveys were omitted from the early-quarter survey. This left us with 33 responses in EQ and 40 responses in LQ. Figure 4.2 shows how EQ and LQ were selected.

We tested for normality of each metric (growth mindset, self-efficacy and perceived relevance) for each of our sample populations EQ and LQ using the Shapiro-Wilk test. We found that self-efficacy was the only metric for which the data was normally distributed in both samples. Due to only one of our metrics being normally distributed across both samples as well as the small sample sizes, we use a set of non-parametric tests to determine differences between groups. We use the Kruskal-Wallis H test[17] to test for differences in our three metrics between demographic subgroups and the Mann-Whitney U test[22] to test for differences in our metrics between the two sample populations EQ and LQ.

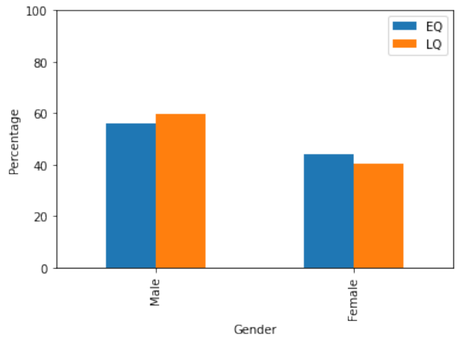
Table 4.1: Percentages of colleges represented in EQ and LQ

College	EQ	LQ
COSAM	67%	63%
CENG	12%	17%
OCOB	9%	11%
CLA	6%	9%
CAFES	6%	0%

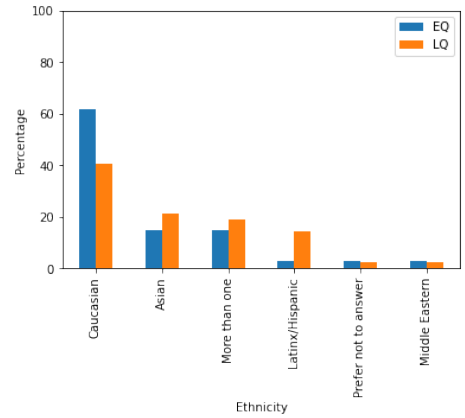
4.1.1 Demographics

In the demographics portion of the survey we collected information about students' *gender, race and ethnicity, year in school,* and *first programming experience.* Due to many individual majors having too few respondents, *college of major* was used as a proxy for discipline of study. For each demographic category, EQ and LQ shared similar percentages of students in most subgroups as shown in Figure 4.3. Table 4.1 shows the percentage breakdowns of colleges represented in EQ and LQ. However, we highlight the demographic subgroups that had significant differences in percentages within EQ and LQ. Due to these differences, we do not assume equal populations which may pose limitations to the conclusions we draw from this study.

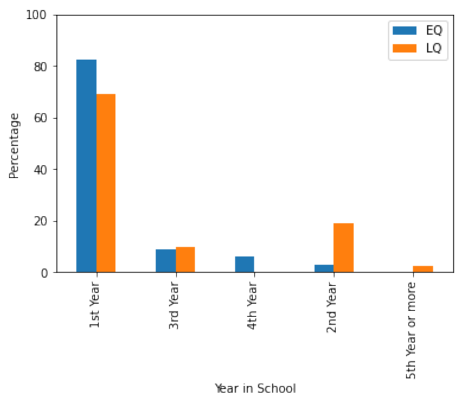
With regards to race and ethnicity, we found EQ to have a significantly higher percentage of Caucasian students (64% versus 43% in LQ). LQ on the other hand had a higher percentage of Latinx/Hispanic students (13% versus 3% for EQ). For year in school, EQ had a higher percentage of first-year students (82% versus 68% for LQ). LQ however had a higher percentage of second-year students (20% versus 3% for EQ). For the remaining data, differences in percentages were below 10%.



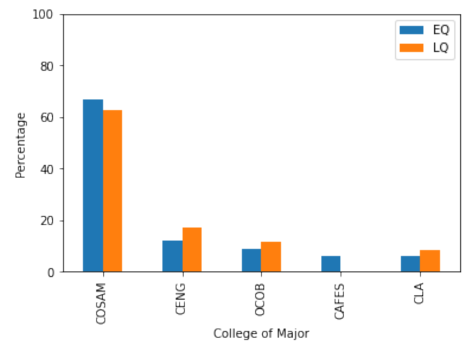
(a) Gender by percentage



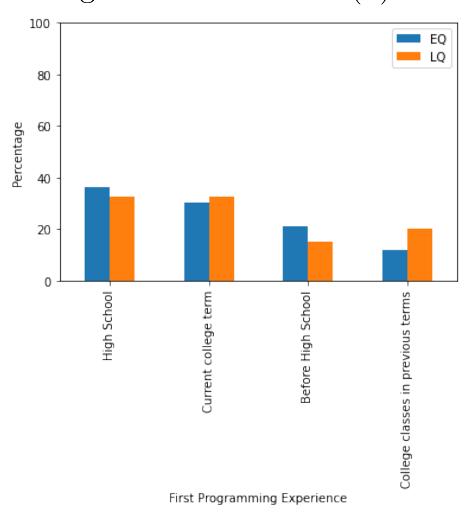
(b) Ethnicity by percentage



(c) Year in school by percentage



(d) College of major by percentage



(e) First programming experience by percentage

Figure 4.3: Percentages of demographic groups represented in EQ and LQ

Table 4.2: Statistics for growth mindset scores for EQ and LQ

Group	Mean	Median	Std. Dev.
EQ	4.30	4.25	0.66
LQ	3.91	4.00	0.89

4.1.2 RQ1: Growth Mindset

On average, students in EQ had fairly high levels of growth mindset earlier in the quarter. The mean and median growth mindset scores were 4.30 and 4.25, respectively (Table 4.2). The Kruskal-Wallis test was used to determine if there was a relationship between a student's growth mindset level and the different demographic categories (gender, race and ethnicity, year in school, the college they belong to and prior experience). For every demographic category, the test revealed no statistically significant difference in growth mindset between the subgroups.

On average, students in LQ had mid-high levels of growth mindset. The mean and median growth mindset scores were 3.91 and 4.00, respectively (Table 4.2) which is slightly lower than those of students in EQ. LQ also had higher frequencies of scores that were below 3.0.

In our Mann-Whitney test however, a statistically significant difference was found between EQ and LQ *(Ueq=842.0, Ulq=478, p=0.04)*. This difference can be seen in the distribution in Figure 4.4. Non-majors in CS1 had high levels of growth mindset when assessed at the beginning of the quarter but had slightly lower levels growth mindset when assessed at the end of the quarter.

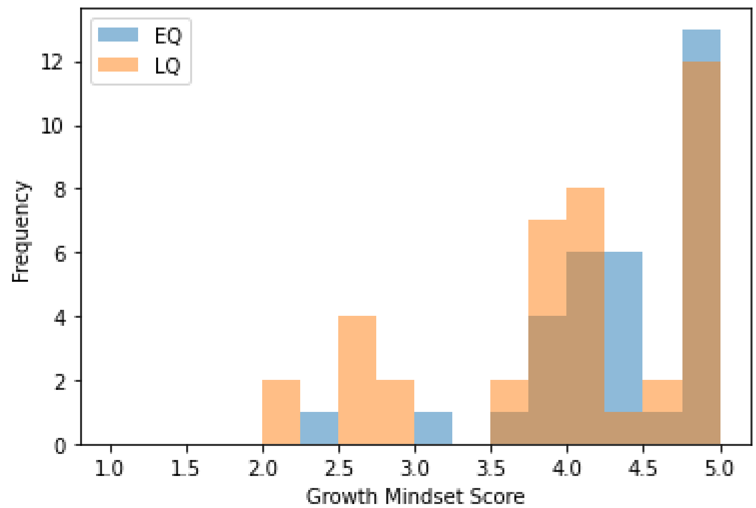


Figure 4.4: Distribution of growth mindset scores in EQ and LQ

4.1.3 RQ2: Self-efficacy

On average, students in EQ had mid-high levels of self-efficacy. The mean and median self-efficacy scores were 3.71 and 3.75, respectively (Table 4.3) and no statistically significant difference in self-efficacy was found between each of the demographic subgroups.

On average, students in LQ also displayed mid-high levels of self-efficacy with mean and median self-efficacy scores of 3.33 and 3.50, respectively (Table 4.3). However this time, we found a statistically significant difference in self-efficacy between men and women *(H=5.155, p=0.023)*.

In EQ, both groups skewed toward the higher end of the self-efficacy scale with women actually having higher mean and median growth mindset scores than men (Table 4.4). Most women in EQ also had scores above 4.0 in EQ (Figure 4.6). By contrast, we found that in LQ, women's self-efficacy scores were significantly lower than men's. Men in LQ had significantly higher frequencies of scores in the higher end of the self-efficacy scale while women had higher frequencies of scores in the middle and lower

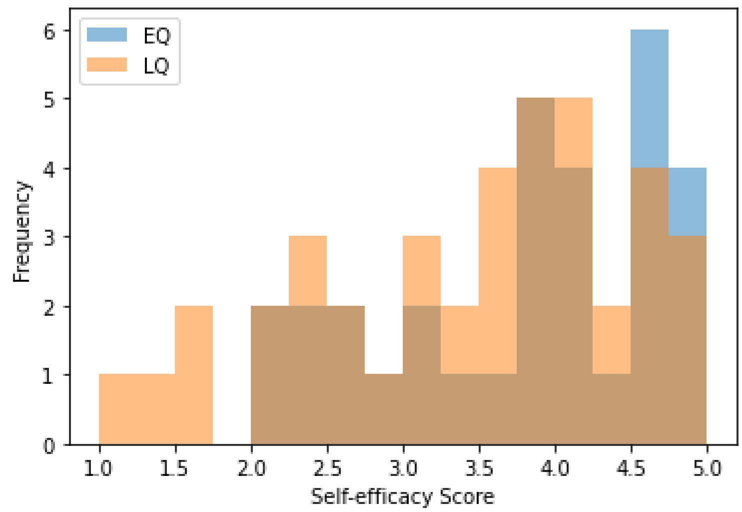


Figure 4.5: Distribution of self-efficacy scores in EQ and LQ

Table 4.3: Statistics for self-efficacy scores for EQ and LQ

Group	**Mean**	**Median**	**Std. Dev.**
EQ	3.71	3.75	0.94
LQ	3.33	3.50	1.06

end (Figure 4.7). This finding is in agreement with the results of Lishinski et al.'s study [19] suggesting that women's self-efficacy is much more malleable than men's in introductory CS. Our results show that this may apply not only to CS majors but to non-majors as well.

The results of our Mann-Whitney test showed no statistically significant difference in self-efficacy between EQ and LQ. This difference can be seen in the distribution in Figure 4.5.

Table 4.4: Statistics for self-efficacy in EQ and LQ by gender

Group	**Gender**	**Mean**	**Median**	**Std. Dev.**
EQ	Male	3.65	3.75	0.88
	Female	3.79	4.00	1.05
LQ	Male	3.58	3.75	0.90
	Female	2.95	3.00	1.18

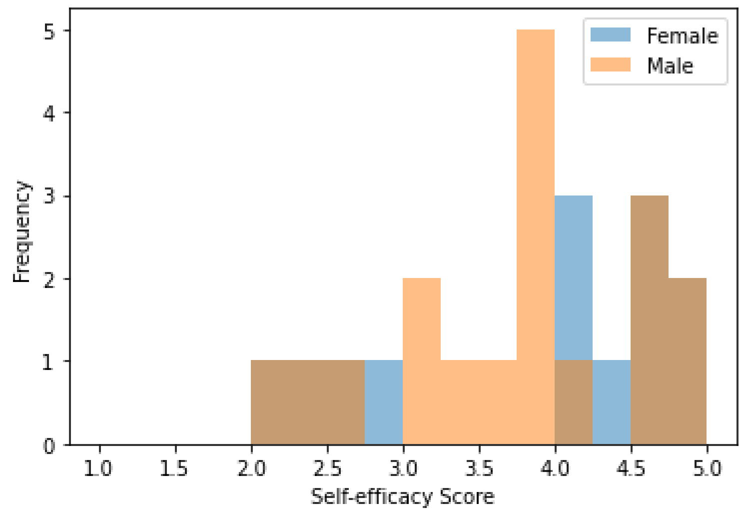


Figure 4.6: Distribution of self-efficacy scores in EQ by gender

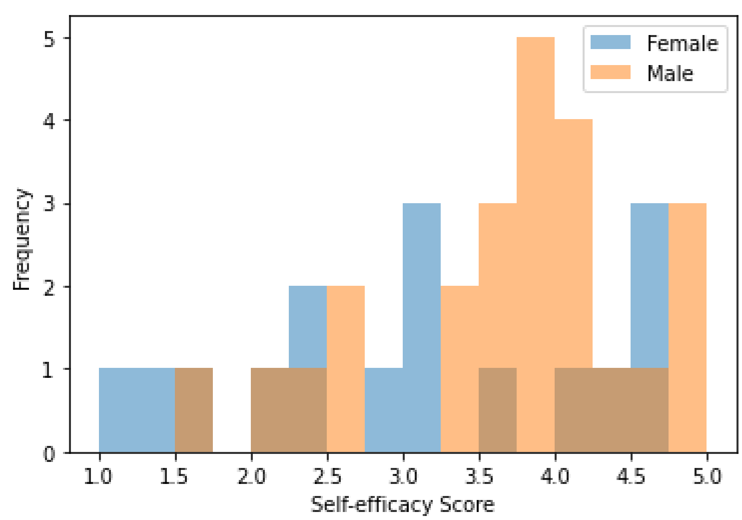


Figure 4.7: Distribution of self-efficacy scores in LQ by gender

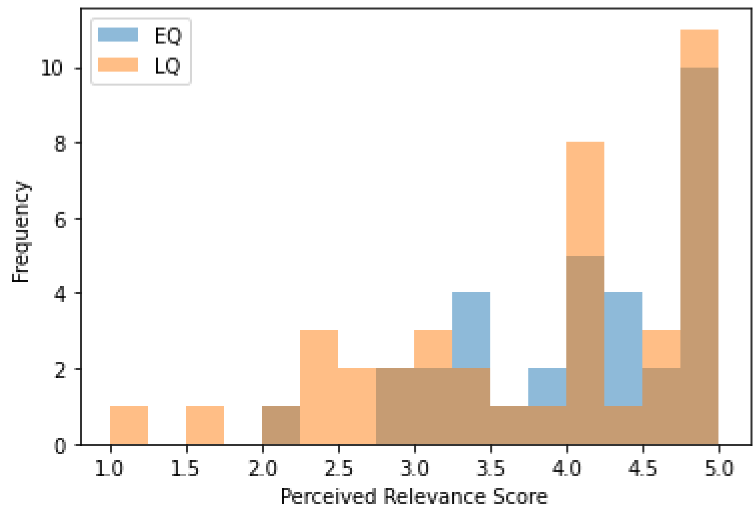


Figure 4.8: Distribution of perceived relevance scores in EQ and LQ

4.1.4 RQ3: Perceived relevance

On average, students in EQ felt that CS1 had a high level of relevance to their general interests as well as academic and professional careers. The mean and median perceived relevance scores were 4.02 and 4.00, respectively (Table 4.5) and no statistically significant difference in perceived relevance was found between subgroups for any of the demographic categories in EQ.

On average, students in LQ felt that CS1 had a mid-high level of relevance to their interests and career with mean and median perceived relevance scores of 3.70 and 4.00, respectively (Table 4.5). Although this suggests a slight decrease, our Mann-Whitney test showed no significant difference in perceived relevance between students in EQ and students in LQ. This distribution can be found in Figure 4.8.

Our tests also showed no significant difference between demographic subgroups in LQ. However, we found the results from testing groupings by College *(H=6.878, p=0.076)* to warrant a closer look. Because this is a study of non-majors, it is important to

Table 4.5: Statistics for perceived relevance scores for EQ and LQ

Group	Mean	Median	Std. Dev.
EQ	4.02	4.00	0.81
LQ	3.70	4.00	1.09

determine whether our data suggests that certain colleges find CS1 to be significantly more or less relevant.

While observing the scores for perceived relevance by college, we found that one particular college may have found CS1 to be less relevant than students of other colleges did. For all five colleges represented (COSAM, CENG, OCOB, CAFES and CLA), the median score for perceived relevance was lower among students who were assessed during the end of the quarter than those of students assessed at the beginning of the quarter. However, while most colleges saw decreases which were within .5 points, the median perceived relevance score for the College of Liberal Arts (CLA) went from 4.63 in EQ to 2.75 in LQ (a 1.88 point difference). These findings require further research to determine whether they are more widespread as the CLA only accounts for 2 responses in EQ and 3 responses LQ. These low response rates may themselves be indicative of low perceived relevance of CS to CLA students.

In addition to these scores, which allow us to view the experiences of non-majors in CS1 from a quantitative lens, we examined students' free response data in which they elaborated on their responses to questions about the relevance of CS1. Among both EQ and LQ students, responses were overwhelmingly positive.

A majority of students in both EQ and LQ reported to having a good experience with CS1 and found the course material to be relevant to their general interests. Notably, 33 out of the 76 students in both EQ and LQ felt that CS1 played an important role in their academic discipline as well as their future careers. Specific career disciplines which were often mentioned include data/statistics, bioinformatics and UI/UX. 7 students in LQ even reported to either wanting to, thinking about or being in the process of switching to a computing major or pursuing a computing minor. Conversely, 4 students in LQ reported to only having taken the course to fulfill a degree requirement and expressed no desire to further pursue computing in other forms.

- *"I'm an information systems concentration and I think that I want to use this technical knowledge in my career"*
- *"I just started minoring in bioinformatics and this course is giving me a foundation to later courses which I will end up applying to biochemistry. I would like to eventually go into a career in bioinformatics."*

Despite students who were assessed at the end of the quarter having lower levels of growth mindset and self-efficacy than those assessed at the beginning of the quarter, perceived relevance remained relatively the same. Although some students were highly doubtful to return to a computing environment, an overwhelming majority of students had positive attitudes towards the course at the end and found its topics to be very relevant to their lives.

4.2 Within-Subjects Analysis

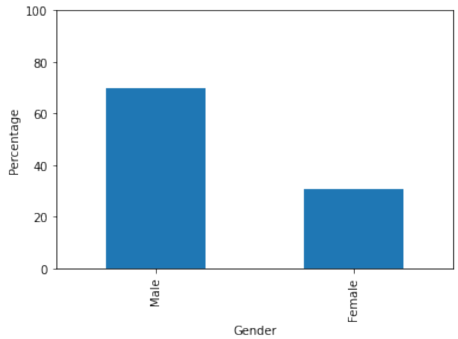
In the previous section, we examined the differences in responses of students in two independent populations EQ and LQ. We saw slight differences in growth mindset and self-efficacy in students during the early quarter and late quarter. However, our conclusions may be limited by our small, independent samples.

In this section, we do a within-subjects analysis to see if our findings here replicate the findings from the previous section. This sort of analysis is important for examining how individual students' growth mindset, self-efficacy and perceived relevance actually changed throughout the duration of the course. To do this, we examine the responses of the 22 non-computing majors who responded to **both** the early-quarter and late-quarter surveys.

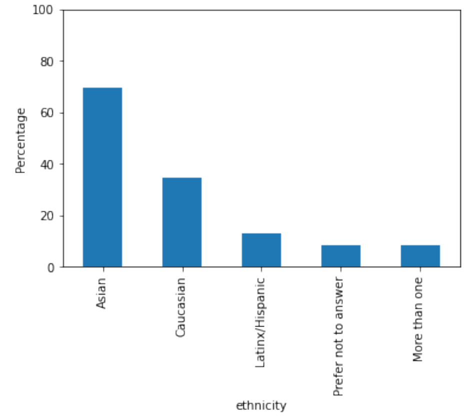
Again, we tested for normality of both early quarter and late quarter measurements of growth mindset, self-efficacy and perceived relevance scores of those who responded to both surveys. Additionally, we tested for normality of the differences of the measurements taken at the two different times. Again, self-efficacy was the only metric that was normally distributed for the early quarter, late quarter and difference measurements. Due to our small sample size and to stay consistent with our analyses in the previous section, we use the Kruskal-Wallis test to test for statistically significant differences between demographic subgroups. To test for statistically significant differences between the early quarter and late quarter measurements within our sample, we use the Wilcoxon Signed Rank test [31] for paired samples.

4.2.1 Demographics

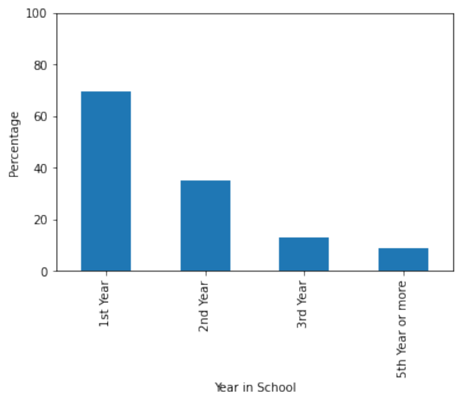
Among students who responded to both surveys, we saw a significantly higher percentage of Asian students compared to Caucasian students, who were the dominant group in both EQ and LQ in our between-subjects analysis. This difference in our population may pose limitations in our findings and the connections we draw to our previous analyses. The complete distributions of these subgroups can be found in Figure 4.9. Table 4.6 shows the percentage breakdowns for colleges represented in the paired samples.



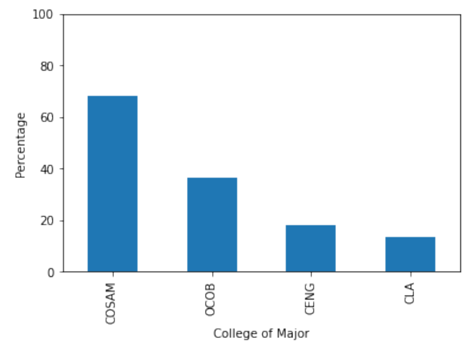
(a) Gender by percentage



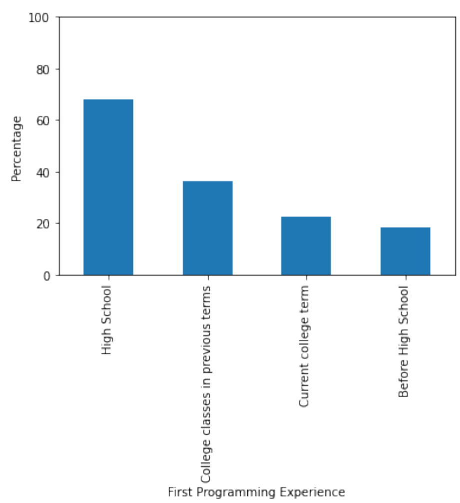
(b) Ethnicity by percentage



(c) Year in school by percentage



(d) College of major by percentage



(e) First programming experience by percentage

Figure 4.9: Percentages of demographic groups represented within subjects

Table 4.6: Percentages of colleges represented within subjects

College	% of Respondents
COSAM	50%
CENG	18%
OCOB	18%
CLA	14%
CAFES	0%

Table 4.7: Statistics for growth mindset scores within subjects in early quarter and late quarter

Time of Measure	Mean	Median	Std. Dev.
Early quarter	4.30	4.50	0.61
Late quarter	3.94	4.00	0.92

4.2.2 RQ1: Growth Mindset

For growth mindset, we found trends that were similar to those we saw in our between-subjects analysis. On average, students had high levels of growth mindset when assessed early in the quarter and mid-high levels of growth mindset when assessed late in the quarter. The mean and median scores for growth mindset were 4.30 and 4.50 early in the quarter and 3.94 and 4.00 late in the quarter, respectively (Table 4.7). We can see that even within the same population, students on average experienced a slight decrease in growth mindset throughout the duration of the course. However, our Wilcoxon Signed Rank test revealed no statistical significance in the difference between the paired observations. These distributions can be seen in Figure 4.10

In addition to purely observing the early quarter and late quarter scores for all students, we also look at the degree by which each student's score changed. Our findings show that students experienced both increases and decreases in growth mindset. However, students who had a decrease in growth mindset did so by a larger factor than students who had an increase in growth mindset. While the average increase was

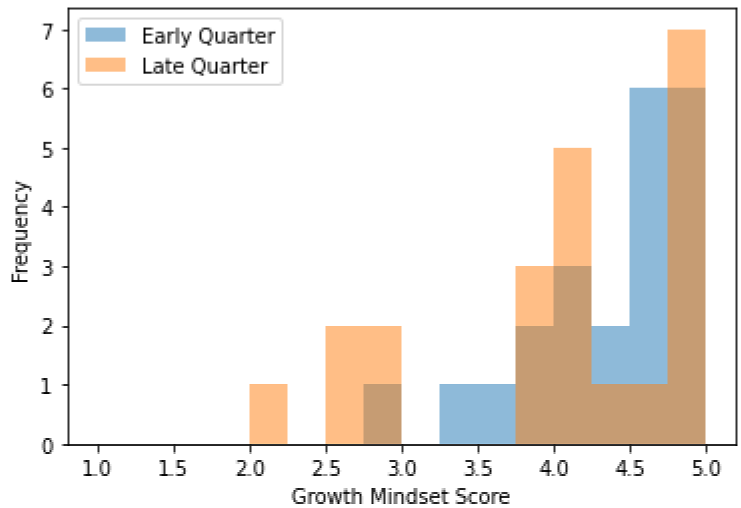


Figure 4.10: Distribution of growth mindset scores within subjects in early quarter and late quarter surveys

by 0.38 points, the average decrease was nearly three times that at 0.95 points. No demographic difference was found in students who experienced a decrease in growth mindset versus students who experienced an increase.

These findings reveal something we were unable to see in the between-subjects analysis which is that not all students experienced a decrease in growth mindset towards the end of CS1. In fact, the number of students who had a decrease in growth mindset was similar to the number of students who had an increase. However, when students experienced a decrease, the difference was more severe.

4.2.3 RQ2: Self-efficacy

With regard to self-efficacy, we saw results which were similar to those we saw in our between-subjects analysis with the exception of gender difference. On average, students in our paired samples had mid-high levels of self-efficacy in both early and late quarter surveys, which is similar to what we saw in our between-subjects analysis. The mean and median scores were 3.90 and 3.88 early in the quarter and 3.53 and 3.75

Table 4.8: Statistics for self-efficacy scores within subjects in early quarter and late quarter

Time of Measure	Mean	Median	Std. Dev.
Early quarter	3.90	3.88	0.64
Late quarter	3.53	3.75	0.90

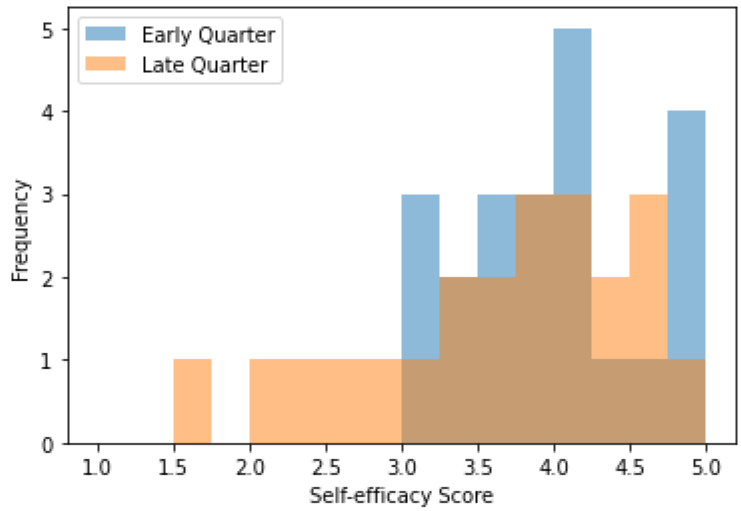


Figure 4.11: Distribution of self-efficacy scores within subjects in early quarter and late quarter surveys

late in the quarter, respectively (Table 4.8). As we saw with growth mindset, students' levels of self-efficacy seemed to, on average, slightly decrease at near completion of the course. However, our Wilcoxon Signed Rank test revealed no statistical significance in the difference between the paired observations. This distribution can be seen in Figure 4.11.

Again, when examining the changes in self-efficacy scores among students, we found that similar numbers of students experienced both decreases and increases in self-efficacy. However, students that had decreases in self-efficacy did so by a larger factor than those who had increases. The average increase was 0.54 points while the average decrease was 0.90 points. Like the results of the previous section, we found that not

Table 4.9: Statistics for self-efficacy within subjects by gender

Time of Measure	Gender	Mean	Median	Std. Dev.
Early Quarter	Male	4.10	4.00	0.62
	Female	3.46	3.25	0.49
Late Quarter	Male	3.42	3.75	0.96
	Female	3.79	4.00	0.71

all students experienced a decrease in self-efficacy but those that did experienced a more severe dip.

Additionally, we found that there was a statistically significant difference in change in self-efficacy between men and women *(H=6.013, p=0.014)*. This difference however was unlike what we found in our between-subjects analysis. While women had an average increase of 0.32 points, we found that men had an average decrease of 0.67 points. Women's self-efficacy was found to be lower than men's early in the quarter but higher than men's late in the quarter. Although these differences were not found to be statistically significant (Table 4.9), they are contradictory to what we saw in our between-subjects analysis where women were found to have significantly lower levels of self-efficacy than men late in the quarter. This prevents our study from having conclusive results from the two analyses with regard to gender differences in self-efficacy.

4.2.4 RQ3: Perceived relevance

On average, students in our paired samples had high levels of perceived relevance with mean and median scores of 3.98 and 4.00 in the early quarter survey and 4.03 and 4.00 in the late quarter survey, respectively (Table 4.10). As we saw in our between-subjects analysis, average perceived relevance of CS1 in students' lives remained almost exactly the same throughout the duration of the course and even had

Table 4.10: Statistics for perceived relevance scores within subjects in early quarter and late quarter

Time of Measure	Mean	Median	Std. Dev.
Early quarter	3.98	4.00	0.65
Late quarter	4.03	4.00	0.76

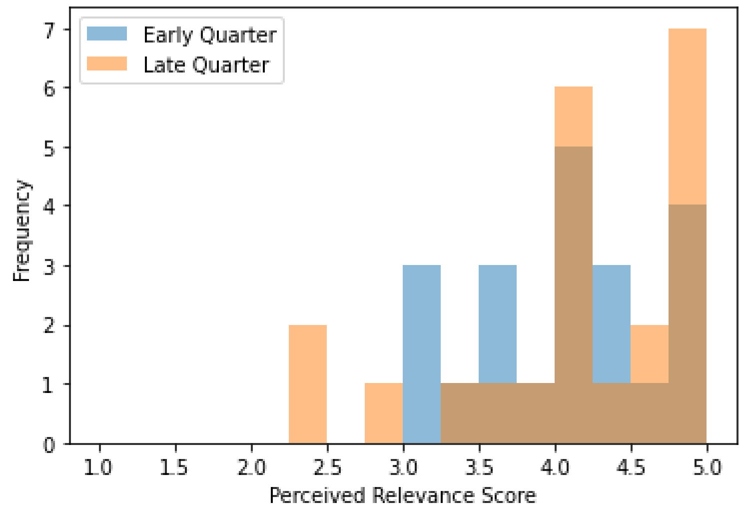


Figure 4.12: Distribution of perceived relevance scores within subjects in early quarter and late quarter surveys

a slight increase. Our Wilcoxon Signed Rank test also revealed no statistical significance in the difference between the paired observations. This distribution can be seen in Figure 4.12.

Contrary to what we saw with regards to growth mindset and self-efficacy in our within-subjects analysis, we found that 70% of students actually experienced an increase or no change in their perceived relevance of CS1. We also saw an inverse effect where the average increase was 0.63 points while the average decrease was only 0.33 points. Most students found that CS1 was just as relevant if not more relevant to their academic and professional careers as well as their general interests.

No statistically significant difference was found between each of the demographic subgroups for change in perceived relevance.

Chapter 5

DISCUSSION

Based on our analyses in the previous section, we present two key findings of our research. In this section, we discuss the takeaways from our analyses which led us to these findings, how they compare to findings in previous research, and provide some recommendations on how these findings can be used to help make CS education for non-majors a better experience. The findings are as follows:

- **Non-majors entered CS1 with favorable levels of growth mindset and self-efficacy, but these levels changed throughout the duration of the course.**
- **Regardless of positive or negative changes in growth mindset and self-efficacy, non-majors found CS1 to be highly relevant to their lives.**

Non-majors entered CS1 with favorable levels of growth mindset and self-efficacy, but these levels changed throughout the duration of the course. In our analyses, we found that most non-majors in CS1 skewed towards high levels of growth mindset and self-efficacy in the first weeks of the course. Students came into the course ready to learn and believed that their knowledge and skills within CS could be expanded, regardless of what their prior experience had been. They were confident in their ability to learn the material presented to them.

However, we found that growth mindset and self-efficacy levels changed for most students towards the end of the quarter. In our within-subjects analysis, about as many students had a decrease in growth mindset as students who had an increase in growth mindset. For self-efficacy however, the number of students who had a decrease was double the number of students who had an increase. For both metrics, students who had decreased growth mindset and self-efficacy did so at a higher magnitude than those who had increases. We acknowledge that this effect of decreased growth mindset and self-efficacy may be shared across college courses in general and not just introductory CS. Limeri et al. have observed similar effects at a larger scale among students in an organic chemistry course [18].

We find these results to be both encouraging and concerning considering the observations made by Lishinski et al. [19] in which CS1 students were found to be in a feedback loop driven by their self-efficacy, goals and strategies. These things in turn affect students' performance and vice-versa. Because a majority of our students went into the course with expectations to succeed we expected that many would indeed perform well and were confirmed in their expectations. However, our findings create concern over the group of students who under-perform then change their beliefs on their ability, further affecting their performance. If more students experience decreased self-efficacy at higher magnitudes, it is possible that similar effects can exist for performance.

From the early quarter score distributions of growth mindset and self-efficacy, we have seen that non-majors in CS1 come into the course with confidence and the belief that they can grow their knowledge of CS. To preserve these beliefs, we echo Gorson and O'Rourke's [11] belief that exposure to mindset and social cognitive theories may help better solidify students' beliefs about their abilities. In addition, we suggest that interventions for self-efficacy be explored for students who are at risk of being caught in a negative feedback loop.

Regardless of positive or negative changes in growth mindset and self-efficacy, non-majors found CS1 to be highly relevant to their lives. Students' attitudes towards CS1 were overwhelmingly positive and remained so through the duration of the course. These results were consistent throughout both between-subjects and within-subjects analyses. We find this to be encouraging but not surprising because many students belong to "computing adjacent" disciplines such as Math, Statistics and Electrical Engineering.

Many students brought up ways in which CS1 was relevant to their academic and career goals.

- *"I can use this class for my bioinformatics minor"*
- *"I am minoring in Bioinformatics and I am hopeful that it will help immensely in my future classes as well as my future career."*
- *"While programming has never been in the forefront of my interests, I do believe learning programming will be very applicable to me since I want to go into financial/data analysis. And as a mathematics major, learning how to work with programming to compute the more lengthy tasks rather than computing it by hand. And as of week two, CPE 101 has been very fun so far and really piques my interest."*
- *"I am a statistics major, and I believe once I receive the full content of this class I will understand how to use it in my future jobs and courses. At this point I am not sure how it will benefit me in my chosen field, so that's why I can't completely agree.*

Even among students who had decreased sense of self-efficacy towards the end of the quarter, most found the material in CS1 to be useful and interesting. One student even mentioned a desire to switch into computing.

- *"I'm an information systems concentration and I think that I want to use this technical knowledge in my career"*

- *"I have never been too interested in computer science, and in previous classes I have fallen behind. I know that it is useful for my major as more Stats majors are learning and using python, but the setbacks I face can make me lose motivation. I know there are many useful lessons from this class, so it is up to me to take some time to learn them all."*

- *"While taking this class has actually boosted my confidence that I am capable of coding, I have been able to succeed with a LOT of help and would not feel comfortable doing a lot of this stuff outside of a classroom. But I'm concentrating in UX/UI for GrC so I'm glad I understand how computers work more than a lot of my peers."*

- *"In GrC but trying to switch to something that involves coding."*

Based on these responses, the role that relevance plays on non-majors' ability to see the importance of introductory CS is clear. Even though the course does not explicitly tap into interdisciplinary contexts, students were well aware of how the skills they learn can be used outside of just CS. We believe that by following Fisher and Margolis' [8] recommendation to "revise assignments, courses, and curricula to ensure that they serve the interests and orientations of students who are studying computing because of what it can do," we can bring forth more paths for students of different backgrounds to pursue computing outside of the traditional fashion.

Chapter 6

THREATS TO VALIDITY AND FUTURE WORK

One of the threats to validity to our study is the context in which the research was conducted. Our data was collected during a global pandemic due to COVID-19. All courses were held in online learning environments in the midst of a challenging time. We cannot say what specific effects this may have had on students' academic experience and can only speculate that this different environment has impacted students' learning.

Another threat to validity is the sample size of our study. Not as many students responded to the late-quarter survey and significantly fewer responded to both surveys (23). In an effort to strengthen our study, we performed between-subjects and within-subjects analyses using different subsets of students who responded to the two surveys. As a result, some students' responses were accounted for in both analyses.

Lastly, self-reporting of metrics may pose another threat to validity. Students' responses to the early-quarter survey may be inconsistent with their responses to the late-quarter survey. Namely, a growth mindset, self-efficacy or perceived relevance score of 5 in the early-quarter survey may not mean the same in the late-quarter survey. Students may also answer questions in a way that does not completely reflect their actual self-beliefs.

Although our findings only reflect a small sample of non-majors in CS1 under abnormal circumstances, we believe them to be solid grounds for further research into the experience of non-majors in introductory CS. Some future works to consider are as follows:

- Larger-scale comparative research and multi-year data collection of both CS majors' and non-majors' experiences in introductory CS courses,
- qualitative research into gender differences in self-efficacy in CS,
- exploring non-traditional methods of teaching CS such as mastery learning, and
- exploring the effects of including of mindset and self-theories in the CS curriculum.

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APPENDICES

Appendix A

SURVEY

Included below is the full text of the survey that was distributed to students.

Self-Efficacy and Mindset Survey

INFORMED CONSENT TO PARTICIPATE IN A RESEARCH PROJECT:

“Introductory CS Student Survey”

INTRODUCTION

This form asks for your agreement to participate in a research project on the self-efficacy and learning mindsets of students who are taking an introductory CS course. Your participation involves taking part in a survey and allowing the use of your answers in research and analysis. It is expected that your participation will take approximately 5-7 minutes. These responses are not anonymous and ask for your Cal Poly username. However, your responses will only be accessible by the investigators of this research and will only be used in aggregate form. There are some minimal risks anticipated with your participation. You may personally benefit from this study and others may benefit from your participation. If you are interested in participating, please review the following information.

PURPOSE OF THE STUDY AND PROPOSED BENEFITS

· The purpose of the study is to gauge the self-efficacy, learning mindsets and motivation of students who are taking introductory CS.

· Potential benefits associated with the study include a better understanding of how self-efficacy and learning mindset affect student outcomes in introductory CS.

YOUR PARTICIPATION

· If you agree to participate, you will be asked to take part in a survey that will assess your computing self-efficacy and learning mindset.

· Your participation will take approximately 5-7 minutes.

PROTECTIONS AND POTENTIAL RISKS

· Please be aware that you are not required to participate in this research, refusal to participate will not involve any penalty or loss of benefits to which you are otherwise entitled, and you may discontinue your participation at any time. You may omit responses to any questions you choose not to answer.

There is a minimal risk to your reputation or status should your data be disclosed along with your identity. There also is a minimal possibility of emotional distress should any of the questions trigger unpleasant thoughts or feelings.

Your personal responses will only be accessible by the investigators of this study and will only be used in aggregate form. However, they can only be protected to the extent allowed by Google forms which is not a secure survey platform. Data will be stored in Google Drive and deleted after a period of 3 years or at the participant's request.

RESOURCES AND CONTACT INFORMATION

· If you should experience any negative outcomes from this research, please be aware that you may contact Campus Psychological Services at 805.756.2511, for assistance.

· This research is being conducted by Kevin Yoo, Student and Ayaan M. Kazerouni, PhD. Assistant Professor in the Department of Computer Science and Software Engineering at Cal Poly, San Luis Obispo. If you have questions regarding this study or would like to be informed of the results when the study is completed, please contact the researcher(s) at Ayaan M. Kazerouni at ayaank@calpoly.edu or Kevin Yoo at jyoo18@calpoly.edu.

· If you have any concerns about the conduct of the research project or your rights as a research participant, you may contact Dr. Michael Black, Chair of the Cal Poly Institutional Review Board, at (805) 756-2894, mblack@calpoly.edu, or Ms. Trish Brock, Director of Research Compliance, at (805) 756-1450 or pbrock@calpoly.edu.

AGREEMENT TO PARTICIPATE

If you are 18 years of age or older and agree to voluntarily participate in this research project as described, please indicate your agreement by completing the attached survey. Please retain a copy of this form for your reference. Thank you for your participation in this research.

* Required

1. What is your Cal Poly username? (Your Cal Poly email without the "@calpoly.edu") *

2. 1. What is your year in school? *

Mark only one oval.

- 1st Year
- 2nd Year
- 3rd Year
- 4th Year
- 5th Year or more
- Graduate

3. 2. What is your major? *

Mark only one oval.

- Computer Science
- Computer Engineering
- Software Engineering
- Graphic Communications
- Other: ____________________

4. 3. What is your gender? *

Mark only one oval.

- Female
- Male
- Non-binary
- Prefer not to answer
- Other: ____________________

5. 4. What is your ethnicity? Check all that apply. *

Check all that apply.

- Caucasian
- Black/African America
- Latinx/Hispanic
- Asian
- Native American
- Native Hawaiian or Pacific Islander
- Prefer not to answer

Other: ____________________

6. 5. When was your first exposure to programming or programming environments? *

Mark only one oval.

- Before High School
- High School
- College classes in previous terms
- Current college term
- Prefer not to answer

Read each statement below then check the corresponding option that shows how much you agree with each statement. There are no right or wrong answers.

7. You have a certain amount of computing ability, and you can't do much to change it.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree						Strongly Disagree

8. No matter who you are, you can significantly change your computing ability.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree						Strongly Disagree

9. You can learn new things but you can't really change your level of computing ability.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

10. No matter what level of computing ability you have, you can always change it quite a bit.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

11. I believe I will receive an excellent grade in this class.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

12. I'm certain I can understand the most difficult material presented in the readings for this course.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

13. I'm confident I can do an excellent job on the assignments and tests in this course.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

14. I'm certain I can master the skills being taught in this class.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

For numbers 1-5 below, read each statement then check the corresponding option that shows how much you agree with each statement. There are no right or wrong answers.

15. 1. CSC 101 is relevant to my general interests.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

16. 2. CSC 101 is relevant to my interests that are related to my major.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	◯	◯	◯	◯	◯	Strongly Disagree

17. 3. Taking CSC 101 makes me want to learn more about programming in general.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	☐	☐	☐	☐	☐	Strongly Disagree

18. 4. CSC 101 has taught me many skills that I will likely use in future courses or jobs.

Mark only one oval.

	1	2	3	4	5	
Strongly Agree	☐	☐	☐	☐	☐	Strongly Disagree

19. Please elaborate on your answers to items 1-4 in this section.

____
____
____
____
____

20. What are your motivations for taking CSC 101.

Check all that apply.

- ☐ It was required.
- ☐ I wanted to learn more about computing in the context of my major.
- ☐ I wanted to learn how to program or code.
- ☐ I want to pursue a career which deals with computing and my major.

Other: ☐ ______________________