Identifying Factors That Influence Engineering Students' Outcome Expectancy and Learning Self-Efficacy in a Flipped CS1 Course

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Abstract

As the importance of learning computational skills increases for undergraduate engineering students, it is important to explore the factors that influence their confidence in their ability to learn and their perception of their expected performance in a course. In technical and problem-solving-based courses, students often have preconceived beliefs about their abilities and performance. In the context of programming and for this study, we define learning self-efficacy as students' confidence in their ability to solve problems and learn to program. We also define outcome expectancy through students' perceptions of their expected final grades within a course. Students' learning self-efficacy and outcome expectancy are fundamental motivation constructs that may affect their participation in a course and influence their approach toward learning and performance. Although in the past, researchers have studied motivational and other factors like prior programming experience, self-regulation, level of practice, and task value, to predict students' performance within a course, the literature is scarce on factors that underpin engineering students' motivational beliefs related to learning programming. In this analysis, we explore the influence of prior programming experience (PPE), academic standing (GPA), and gender on students' learning self-efficacy and outcome expectancy. We analyze the data of 600 engineering students enrolled in a CS1 course and find that gender and PPE are statistically significant factors that influence students' learning self-efficacy. We also find that learning self-efficacy and GPA are statistically significant predictors of outcome expectancy. We believe these results will help advance our understanding of engineering students' motivational beliefs and help instructors identify specific groups of students that may need additional support and assistance.

1 Introduction

As the importance of acquiring computational skills increases, there is a growing emphasis on adding more programming and data analysis courses in the undergraduate curriculum, especially for engineering majors [1]. Computer science and engineering education researchers and educators have long been interested in identifying factors that influence and predict students' performance in an introductory programming (CS1) course. There have been multiple studies that have examined an eclectic spectrum of factors ranging from socio-demographic to motivational, behavioral, psychological, and pedagogical [2, 3]. However, the majority of the studies have been conducted on students primarily from computer science majors. Given that students' majors can potentially influence their learning and course experience, exploring the affordances of motivational constructs and how they influence engineering students' approaches toward learning in a CS1 course would be valuable.

Human motivation is a complex construct, and it can entail many sub-factors that can dynamically influence it over a period of time. Many disciplines like psychology, education, athletics, and business study human motivation to understand what causes someone to take action or perform a task. This helps in understanding the agentic underpinnings of action and individual characteristics that propel someone to take action or engage in any activity. In psychology, self-efficacy has been an established construct that, according to Bandura's Social Cognitive Theory, *"refers to beliefs in one's own capabilities to organize and execute the courses of action required to produce given attainments"* [4] in performing a task. Multiple studies in education have shown that individuals with high self-efficacy have higher academic persistence and achievement [5, 6, 7, 8].

Given that self-efficacy is a motivational construct, one thing that is not explored enough is its transitory nature. How does one cultivate and develop self-efficacy in a particular domain? To what extent is initial self-efficacy fixed? And to what extent can someone influence it? We believe there are multiple such contours on which the dynamics of self-efficacy should be tested, studied, and validated so as to understand self-efficacy's multidimensional nature and its ability to impact one's academic outcomes. In this paper, we intend to study two such research questions that take a snapshot of students' self-reported confidence related to learning to program and their own prediction about their final course grade at the beginning of the semester. In particular, we study students' ***learning self-efficacy***, that is, their confidence in themselves to learn in a CS1 course and ***outcome expectancy***, that is their expected final grade in the course. We use the term learning self-efficacy because it refers to students' confidence measured at the beginning of the course. It's a proxy for their perceived ability to solve problems and learn to program. By taking factors like gender, prior programming experience, and GPA, we are interested in analyzing which factors influence a student's outcome expectancy and their learning self-efficacy at the beginning of a CS1 course.

2 Background and Related Work

Various instruments have been developed in computing education to measure and assess self-efficacy [9, 10, 11]. Recently, Steinhorst et al. proposed a more generalized instrument for assessing self-efficacy that is paradigms and language agnostic [12]. Multiple studies have investigated the role of self-efficacy in the context of introductory programming courses [13, 14, 15, 16]. While there have been a number of studies, it should be noted that the landscape of CS1 has been evolving with growing enrollments and a wide variety of programming languages used in the courses. Also, more students can now take CS0/1 in high school compared to some time back [17]. Thus, studying the effect of motivational constructs may differ based on students' past experiences and majors.

In the context of engineering education, a study conducted by Usher et al. found that *"although students may find engineering challenging, their perceived efficacy might benefit from the positive emotions they feel when engaged in their work"* [18]. While there has been an interest in exploring how self-efficacy influences students' retention and persistence in engineering, to the best of our knowledge, no studies specifically study engineering students' confidence in learning to program and their outcome expectancy at the beginning of a CS1 course. While many factors can impact an engineering student's learning experience, exploring how initial perceptions of a course (after accounting for academic standing) may help identify student groups needing more attention and support.

3 Research Questions

With an understanding of factors that are influential to a student's outcome expectancy and learning self-efficacy, instructors can be more informed about the influence of motivational constructs on students learning approaches and success. While some students struggle simply due to a lack of motivation, some struggle because computer programming is a difficult skill for many to comprehend initially[19]. Therefore, this research analyzes the factors that influence students' outcome expectancy and learning self-efficacy at the beginning of a CS1 course. Consequently, our research questions are:

- ***Which factors best predict students' self-reported outcome expectancy (expectation of their final grade) at the beginning of a CS1 course?***
- ***Which factors affect students' self-reported learning self-efficacy at the beginning of a CS1 course based on gender, prior programming experience, and GPA?***

4 Course Context

The data used in this study comes from a two-credit introductory programming course for engineering students that was taught in MATLAB. This class was taught using the flipped classroom model at an R1 research university in the US over four semesters: Spring 2021, Fall 2021, Spring 2022, and Fall 2022. This course has multiple and varying sections, all offering an in-person class subsection (except the Spring 2021 semester, in which the majority of students attended online due to the pandemic). Generally, each of the class sections was capped at 49 students, and most of the students that registered to be in-person still opted to attend the class virtually.

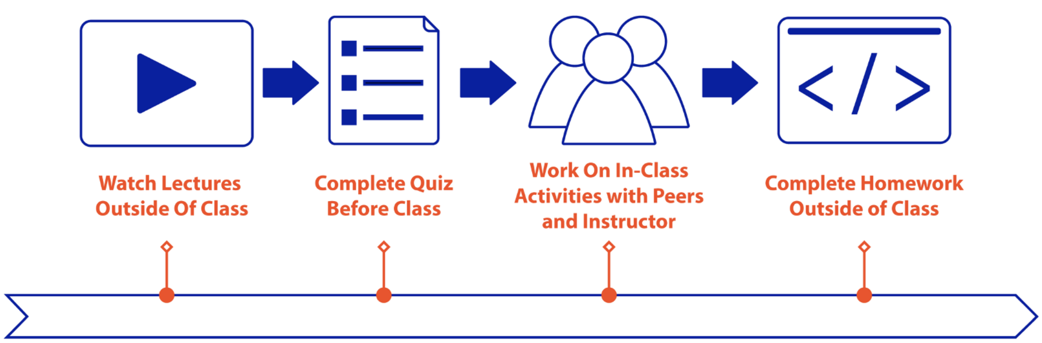

Figure 1: Weekly plan of the CS1 flipped course

Figure 1 shows the standard weekly timeline for the course. Since the course used the flipped classroom model, students were expected to watch module lectures and complete the weekly graded quiz before class. Class time was reserved for reviewing the content taught in the video lectures and completing in-class programming problems with the instructor and peers. Students worked on the module homework assignments outside of class, which were due at the end of the week.

The key programming concepts covered in the modules included input/output, conditionals, while/-for loops, vectors, strings, images, and functions. The course was divided into 14 modules with eight programming-related homework assignments and two exams (a midterm and a final). The last assignment was a cumulative final project.

4.1 Introductory Surveys

Each student was given an introductory survey during the first week of the class. This survey asked for demographic information (gender, prior programming experience (PPE), year in school, GPA, and major), general information (if the student was also taking the lab associated with this course and how many hours of prior programming experience they had), as well as what grade they expected to receive in the course by the end of the semester. Students were given a drop-down menu of achievable grades in the class and asked to choose which grade option they expected themselves to receive. Finally, the students were asked questions about their perceptions of programming and learning preferences. For each question, five options on the Likert scale were given: strongly agree, somewhat agree, somewhat disagree, strongly disagree, and neither agree nor disagree.

5 Demographics

For this study, there were 620 students whose data was collected across four semesters of the introductory programming course, out of which data of 20 students were discarded due to missing information. The number of students whose data was used for this paper was 600. Out of the 600 students whose data was used, 117 (19.5%) came from the Spring semester of 2021, 168 (28.0%) came from the Fall 2021 semester, 139 (23.2%) came from the Spring 2022 semester, and 176 (29.3%) came from the Fall 2022 semester. Of the 600 students, 217 (36.2%) were female, of which 86 (39.6%) had prior programming experience. There were 383 (63.8%) male participants, of which 168 (43.6%) had prior programming experience. Out of the 600 students, a total of 253 (42.2%) students had prior programming experience.

Table 1: Class Composition based on Gender and PPE

	No PPE	PPE	Total
$Female$	131	86	217
$Male$	216	167	383
$Total$	347	253	600

Students were asked to self-report their GPA. GPA was based on a scale of 4, with an “A” being a 4.00, a “B” being a 3.00, a “C” being a 2.00, a “D” being a 1.00, and an “S” being a 0.00. Some classes also used a “+” or “–” system. A “+” adds 0.33 to the base grade, while a “-” subtracts 0.33. For example, a “B+” would quantitatively be a 3.33 (3.00 + 0.33), while a “B-” would be a 2.77 (3.00 - 0.33).

Data was gathered on students' expected majors. Out of a total of 600 students, 311 (51.8%) were mechanical and/or aerospace engineering students, 114 (19.0%) were civil and/or environmental engineering students, 102 (17.0%) were biomedical engineering students and 73 (12.2%) students had other majors. This data can be seen in Figure 2.

Looking at students' academic year, out of a total of 600 students, 164 (27.3%) were first-year students, 376 (62.7%) were second-year students, 43 (7.2%) were third-year students, 14 (2.3%) were fourth-year students, with 3 (0.5%) were students from other years. This data can be seen in Figure 2.

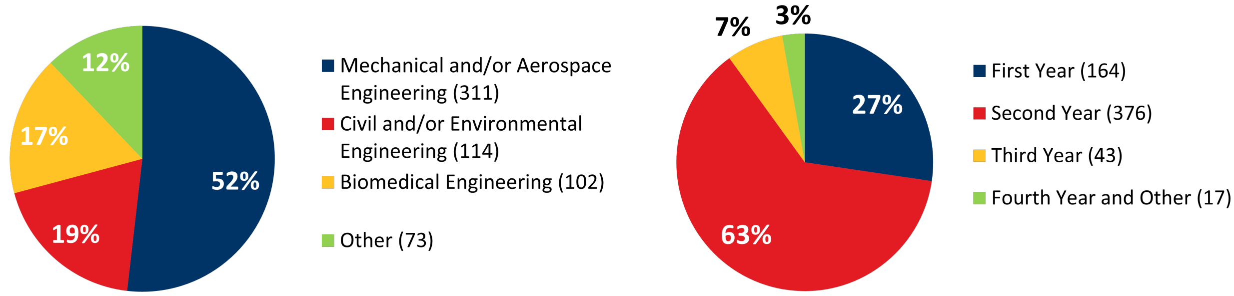

Figure 2: Distribution of Students' Majors (left) and Year (right)

Finally, the 600 students were split up into two groups based on the final grade the students expected to receive prior to taking the course. Of the 600 students, 426 (71.0%) of the students expected to receive an "A" as their final grade in the class, and 174 (29%) of the students expected to receive a grade that was below an "A" as their final grade in the class. This data can be seen in Figure 3.

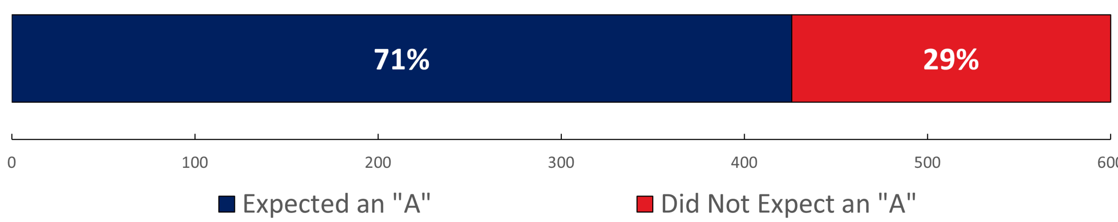

Figure 3: Distribution of Students' Outcome Expectancy

6 Methodology

To understand how gender, PPE, learning self-efficacy, and GPA influence a student's outcome expectancy, data was collected over four semesters via an introductory survey during the first week of class within a CS1 course.

Regarding prior programming experience (PPE), students were given the options: "No prior experience," "Between 1 to 10 hours", "Between 11 to 100 hours", "Between 101 to 500 hours", "I am a software developer," or "I invented a programming language." After a student responded, they were asked for a description of their experience. If a student was determined to have a basic understanding of programming, they were assigned a value of 1. All students having no PPE or very little experience were assigned a value of 0. Students' self-reported PPE and descriptions of their experience were taken into account when assigning the binary PPE values.

Regarding gender, students were given the options: "Male", "Female", and "Other", with the addition of an optional comment box. If a student responded with "Male" they were assigned a value of 1, a student who responded with "Female" was assigned a value of 0, and all other students were assigned a value of 2.

Regarding learning self-efficacy, students were asked to state their agreement level on a Likert-scale of 1-5 with the following statements: *"I feel confident in my ability to solve problems"*, *"I feel confident in my ability to learn programming"*. The students' responses between the two statements were then averaged to assess their overall confidence in their learning abilities (learning self-efficacy).

Regarding GPA, students submitted their grade point averages through a comment box. Those without a given GPA were filtered out of the data. Regarding expected grades, students were given the options to select their expected grade: "A", "B+", "B", "C+", "C", "D+","Other". If a student selected "A", they were assigned an outcome expectancy value of 1, and all other responses were assigned an outcome expectancy value of 0.

We first used logistic regression to analyze the influence of our surveyed variables (GPA, gender, PPE, learning self-efficacy) on the binary dependent variable, outcome expectancy. From those findings, we tested for assumptions and decided on the best model. After our initial analysis using logistic regression, we used linear regression to analyze the influence of gender, PPE, and GPA on the continuous dependent variable, learning self-efficacy. We used Excel and JASP to organize our data and conduct relevant statistical tests.

7 Findings

As described in demographics, out of the total of 600 students, the majority of students, 426 (71%), reported an expected grade of "A", while a significantly sizable group of 174 (29%) reported an expected grade lower than "A". Table 2 provides a general overview of the data collected on outcome expectancy, which highlights the differences between gender and PPE subsections of the class.

Table 2: Expected Grade by Gender and PPE

Gender	PPE	Expected = 0	Expected = 1	Total
$Female$	No	58	78	131
$Female$	Yes	26	60	86
$Male$	No	61	155	216
$Male$	Yes	29	138	167
$Total$		253	347	600

Similarly, Table 3 presents an overview of the data collected on learning self-efficacy (LSE), showing variations between gender and PPE subsections of the class. It is crucial to acknowledge that differences observed between gender groups should not be regarded as definitive evidence of causation and must not be used to make broad generalizations.

Table 3: Learning Self-Efficacy by Gender and PPE

Gender	PPE	LSE
$Female$	No	3.95/5
$Female$	Yes	4.16/5
$Male$	No	4.17/5
$Male$	Yes	4.36/5
$Overall$		4.17/5

RQ1: Which factors best predict students' self-reported outcome expectancy (expectation of their final grade) at the beginning of a CS1 course?

Our logistic regression models are of the form $log\left(\frac{P(Expected=1)}{P(Expected=0)}\right)$ i.e., the dependent variable is the coded binary value of a student's outcome expectancy given some combination of gender, PPE, GPA, and learning self-efficacy.

We used a stepwise selection method to fit five models aimed to explain the odds of a student's outcome expectancy, using two continuous variables (GPA and learning self-efficacy) and two nominal variables (gender and PPE) as predictors. We assessed the goodness of fit using both the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) and selected the best model based on these criteria. The results are given in Table 4. If a coefficient is statistically significant at an alpha level of 0.05, the model proves to be significant, as all of our models do.

Table 4: Logistic Regression for Outcome Expectancy

Model		Deviance	AIC	BIC	p
1	$(Null)$	722.582	724.582	728.979	
2	$(1 + GPA)$	643.283	647.283	656.077	< 0.001
3	$(2 + LSE)$	619.247	625.247	638.438	< 0.001
4	$(3 + Gender)$	610.882	618.882	636.470	0.004
5	$(4 + PPE)$	605.755	615.755	637.739	0.024

Based on the results presented in Table 4, using the AIC and BIC values with significant coefficients, we find that the third model, where GPA and learning self-efficacy explain a student's outcome expectancy, has the best balance between the goodness of fit and model complexity, so we select:

$$log\left(\frac{P(Expected=1)}{P(Expected=0)}\right) = -8.94 + 1.27 \times \textbf{LSE} + 1.29 \times \textbf{GPA}$$

as our best model of the five we fit. Although the fourth model, which includes GPA, learning self-efficacy, and gender, shows a decrease in BIC, the difference is not significant enough to support the more complex model. However, it is important to note that AIC and BIC are measures of model performance and do not inherently tell us whether the model is a good fit for our data. Therefore, we need to perform additional tests to ensure the validity of our selected model.

Logistic regression relies on several basic assumptions, including appropriate outcome structure, observation independence, absence of multicollinearity, linearity of independent variables, and large sample size. In our case, the assumption of appropriate outcome structure is satisfied because our dependent variable, outcome expectancy, is binary. We have a large sample size consisting of the vast majority of our students, 600, within our CS1 course over four semesters, included in the survey data. Learning self-efficacy and GPA both have Variance Inflation Factor (VIF) values that indicate an absence of multicollinearity. To ensure observation independence, we conducted Pearson's correlation coefficient tests to check the correlation between learning self-efficacy and GPA. Table 5 shows that GPA and learning self-efficacy are independent of each other.

Table 5: Correlation Between Learning Self-Efficacy and GPA

			Pearson's r	p
GPA	-	LSE	0.071	0.080

Satisfying the assumption of linearity of independent variables and log-odds, our model confirms the validity of predicting a student's expected grade based on their average learning self-efficacy and GPA. Our findings suggest that a one-unit increase in either learning self-efficacy or GPA is associated with a constant increase in the log-odds of predicting an expected grade of "A", regardless of the initial value of the variables. Furthermore, our results show that students with higher GPAs and higher learning self-efficacy scores are more likely to report an expected grade of "A" than their peers, with low significant contributions of gender or PPE in the final logistic model.

RQ2: Which factors affect students' self-reported learning self-efficacy at the beginning of a CS1 course based on gender, prior programming experience, and GPA?

Improving the understanding of the prior model requires understanding the relationship between learning self-efficacy, gender, and prior programming experience (PPE). We used multiple linear regression to test if gender, PPE, and GPA could significantly predict a student's learning self-efficacy. The linear regression model,

$$\textbf{\textit{Learning Self-Efficacy}} = 3.51 + 0.21 \times \textbf{\textit{Gender}} + 0.2 \times \textbf{\textit{PPE}} + 0.12 \times \textbf{\textit{GPA}}$$

was statistically significant ($R^2 = 0.052, F = 10.87, p < 0.001$). It was found that gender significantly predicted learning self-efficacy ($\beta = 0.22, p < 0.001$). It was also found that PPE could significantly predict learning self-efficacy ($\beta = 0.2, p < 0.001$). Although, it was found that GPA could not significantly predict learning self-efficacy ($\beta = 0.12, p = 0.09$) at an alpha level of 0.05.

Overall, the fitted regression models presented in Table 6 was indicative of a statistically significant relationship between the factors, gender and PPE, and the dependent variable, learning self-efficacy.

Table 6: Linear Regression for Learning Self-Efficacy

Model		Standard Error	p-value
H_0	(Intercept)	0.028	< 0.001
H_1	(Intercept)	0.269	< 0.001
	Gender (1)	0.056	< 0.001
	PPE (1)	0.054	< 0.001
	GPA	0.073	0.093

Furthermore, within the linear regression, we used a two-way ANOVA aimed to explain the odds of a student's learning self-efficacy based on the two nominal variables, gender, and PPE. The two-way ANOVA revealed no statistically significant interaction between the effects of gender and PPE (F = 0.003, p = 0.956). Simple main effects showed that gender did have a statistically significant relationship with a student's learning self-efficacy ($p < 0.01$). Additionally, simple main effects showed that PPE had a statistically significant relationship with a student's learning self-efficacy ($p < 0.01$).

8 Discussion

Figure 4 visually presents the relationship findings. It is important to note that the arrows signify statistically significant relationships. The tail of each arrow corresponds to the independent factor, and the head points to the dependent factor within the variable relationship. Our first research question for this analysis was: Which factors best predict students' outcome expectancy at the beginning of a CS1 course? The results from logistic regression confirm that engineering students' learning self-efficacy and GPA are significant predictors of their expected final grades in a CS1 course. This suggests that academic standing does play a role, but students' confidence in their ability to learn programming is also predictive of their own perception of their performance in the course. This, to an extent, validates the entire premise of self-efficacy as individuals with high self-efficacy are more likely to persist through challenges, and those with less self-efficacy tend to avoid difficulties and getting stuck in a "self-limiting process" [4, 16]. This also confirms earlier findings from studies in other educational contexts [5, 6, 13].

Our second research question was: Which factors affect students learning self-efficacy at the beginning of a CS1 course based on gender, prior programming experience, and GPA? The results from linear regression indicate that students' learning self-efficacy, or their confidence in their ability to learn within a CS1 course, significantly differs based on gender and PPE. These confirm some of the earlier findings that found that students with PPE have higher confidence than students without PPE [11, 15]. The results also confirm that female students may tend to have more *self-critical bias*, evaluating themselves more harshly than others, as found by Gorson et al. [20].

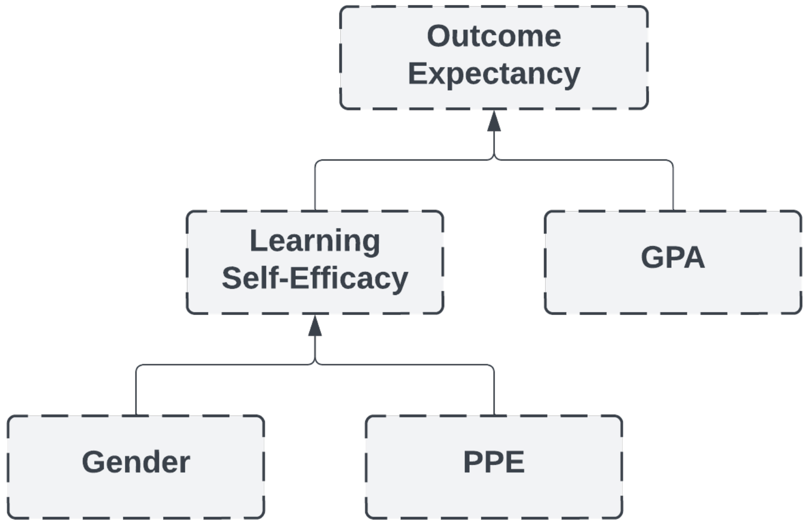

Figure 4: Factors Influencing Students' Outcome Expectancy

9 Limitations

The data was collected from a CS1 course for engineering students for our analysis. The learning self-efficacy of students in a CS1 course may differ from students in other classroom settings, requiring a different approach. Also, the items used to gauge learning self-efficacy were not validated but designed to specifically account for student confidence. This may differ from how other instruments measure self-efficacy. Another limitation is the use of binary coding within the categorization of prior programming experience in our analysis. A student's experience with programming is not a perfectly discrete variable. Although for the purposes of this study, as we focused on understanding the general effect of prior programming experience on a student's reported expected grade, a discrete variable was deemed adequate. Finally, the study was not able to take into account a small group of freshman students who reported a GPA of either "0" or "N/A." This decision was made to preserve the overall accuracy of the analysis.

10 Future Work

As many contributing factors influence a student's outcome expectancy, learning self-efficacy and GPA are only two of many potential factors. We believe the next factors worth exploring are students' motivation about the course and perhaps how their year or major contributes. Additionally, it would be interesting to compare students' learning self-efficacy with their exam averages after the course and how significant of a role a student's learning self-efficacy would have in predicting their actual grade within the overall course. Looking at how a student's self-efficacy or outcome expectancy changes over significant periods of a course may also be a valuable analysis. Another avenue to explore would be to collect more data on the amount of time students spend on a weekly basis for course studies and build explainable models which can help in understanding how perceptions can impact student behavior.

11 Conclusion

As computational skills become increasingly essential, it is important to understand what factors affect students' confidence in their ability to learn to program and how these factors affect students' perception of their own performance in the course. After performing statistical analysis on data given by each student, it was found that both gender and prior programming experience influence students' learning self-efficacy and that students learning self-efficacy and GPA influence students' expected grades. We believe that as the enrollments in CS1 courses continue to rise and as more engineering students engage with computing concepts, it is important to address the self-efficacy needs of students, especially those of female students and students without prior programming experience. Introductory programming courses may leave a long-lasting impression on students about their self-beliefs related to programming. Thus, CS0/1 courses should pay special emphasis on cultivating self-efficacy through pedagogy and instruction as it may, in turn, influence their participation and engagement in the course itself.

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