Learning to Program: Gender Differences and Interactive Effects of Students’ Motivation, Goals, and Self-Efficacy on Performance

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ABSTRACT
Previous research in computer science education has demonstrated the importance of motivation for success in introductory programming. Theoretical constructs from self-regulated learning theory (SRL), which integrates several different types of metacognitive processes, as well as motivational constructs, have proved to be important predictors of success in most academic disciplines. These individual components of self-regulated learning (e.g., self-efficacy, metacognitive strategies) interact in complex ways to influence students’ affective states and behaviors, which in turn influence learning outcomes. These elements have been previously examined individually in novice programmers, but we do not have a comprehensive understanding of how SRL constructs interact to influence learning to program. This paper reports on a study that examined the interaction of self-efficacy, intrinsic and extrinsic goal orientations, and metacognitive strategies and their impact on student performance in a CS1 course. We also report on significant gender differences in the relationships between SRL constructs and learning outcomes. We found that student performance had the expected motivational and SRL precursors, but the interactions between these constructs revealed some unexpected relationships. Furthermore, we found that females’ self-efficacy had a different connection to programming performance than that of their male peers. Further research on success in introductory programming should take account of the unique and complex relationship between SRL and student success, as well as gender differences in these relationships that are specific to CS.

1. INTRODUCTION
Self-Regulated learning (SRL) constructs have been found to be important factors that can help predict students’ academic outcomes [42]. SRL refers to a number of different student characteristics and behaviors (e.g. motivational characteristics, goal-setting behavior, metacognitive self-regulation, and cognitive strategies) that reciprocally interact with one another over time. Previous research in computer science (CS) education has examined motivation and subcomponents of SRL as possible predictors of success, particularly in the context of introductory programming courses [9, 46]. Results from this research have shown that SRL and motivational constructs are useful for predicting programming success. However, these previous studies have mainly focused on examining the relationships between individual SRL constructs and course outcomes, rather than investigating how multiple components of SRL interact in introductory programming students over time as they learn to program. A detailed examination of the relationships and between motivation, SRL, and student CS outcomes requires a more complex structural model than what has previously been used. This model should also include repeated measures of the important constructs to capture reciprocal effects as students move through the process of learning to program. Therefore, the goal of this study was to provide such an analysis, detailing the relationships between SRL constructs in an introductory programming course. Furthermore, previous research has suggested that there are gender differences with respect to self-efficacy which may be important in learning to program [11, 53]. Therefore, this study also investigated gender differences in the relationship between self-efficacy and performance to see if any conclusions could be drawn about gender differences in the way that students approach an introductory programming course.
1.1 Research Questions

- RQ1: What are the relationships between self-efficacy, goal orientation, metacognitive strategies, and course outcomes in introductory cognitive programming students?
- RQ2: How does self-efficacy relate to programming performance, and how does this relationship change over time in CS1?
- RQ3: Are there gender differences in the ways that self-efficacy affects performance in CS1?

2. LITERATURE REVIEW

2.1 Self Regulated Learning: Motivation, Goals, and Metacognitive Strategies

Self-regulated learning theory (SRL) is a broad theoretical framework consisting of a number of behavioral (e.g., goal setting, strategy use) and affective (e.g., motivational states, self-efficacy) characteristics of students. SRL also includes students’ views of the learning process; a self-regulated student is someone who is behaviorally, metacognitively, and motivationally active in his/her own learning ([63], as cited in [64]). Within the SRL framework, motivation and learning strategies are an essential part of students’ academic performance [64]. Use of metacognitive strategies is key as well. Self-regulated learners are characterized by their use of metacognitive strategies to achieve academic goals, and their awareness of the connection between these strategies and learning outcomes [64]. Most of all, self-regulated learners are responsive to feedback from the learning process, modifying their strategies and self-beliefs through self-monitoring of their learning outcomes. In summary, SRL is a theory of effective learning that includes motivation, goal-setting behaviors, and metacognitive strategies, in an iterative process that uses self-monitoring and feedback to modify the application of these learning behaviors. Hence, explaining student learning involves exploring the relationships between these cognitive, affective, and behavioral dimensions.

2.1.1 Motivation: Self-Efficacy

Self-efficacy is an important motivational construct that has its origins in Bandura’s social-cognitive theory [4, 5]. Bandura originally presented self-efficacy as the belief that one can successfully execute behaviors needed to produce a desired outcome [4]. Self-efficacy beliefs determine the amount of effort people are willing to expend and how well they cope and persist in the face of challenges [4]. Within Bandura’s social-cognitive theory, self-beliefs play a self-regulatory role, mediating between goals or values and the behavior that individuals engage in to pursue those goals or values [5]. The strength of this framework is that weak linkages between prior ability and achievement are often explained by these sorts of self-beliefs [5].

Since Bandura’s original discussion of self-efficacy [4], it has become one of the most important motivational variables that helps explain the relationship between past performance and future results in education research ([43], see also [39, 38, 14, 2]). Self-efficacy is related to a number of other self-beliefs (e.g., self-concept, attributions of success and failure) that are also important in motivation theory, but it differs in that self-efficacy beliefs are more context and task specific than other self-beliefs, which are more global characteristics of individuals [35]. The specificity of self-efficacy beliefs is relevant for their use as a predictor of performance, as more general expectancy self-beliefs tend to be more weakly related to student outcomes [5].

The importance of self-efficacy in predicting academic success and choices has been well documented in a number of subject areas, such as mathematics [38], science [14], and language arts [39]. For example, students’ sense of self-efficacy in mathematics has been shown to be more significantly related to their continuing to pursue mathematics than their prior math achievement [38]. Choice of mathematics and science careers has also been found to be strongly predicted by self-efficacy beliefs [31]. Valentine et al. conducted a meta-analysis on the effects of self-efficacy on achievement outcomes and found a consistently significant, albeit small, effect across disciplines, controlling for prior achievement [55]. However, the authors note that in practice, so-called self-efficacy measures often include a mixture of more task specific and more global measures of self-concept, which would cause a shrinkage from the true self-efficacy effect.

Research has also examined the accuracy of self-efficacy beliefs, showing that overconfident self-efficacy beliefs can have detrimental effects on later performance [37]. Prior work has suggested that self-efficacy influences performance by initiating more adaptive behaviors and causing students to pursue more opportunities for practice and feedback [42]. Along these lines, self-efficacy has been shown to be related to more resiliency in response to complex and difficult tasks. Self-efficacy has strong effects on transfer performance as well. A study by Ford et al. found effects of self-efficacy on transfer performance that went beyond the effects of knowledge and skills obtained on the original task [21].

2.1.2 Goal Setting: Goal Orientations

Another important component of self-regulated learning theory is goal orientation, which refers to the types of outcomes students desire for academic achievement situations. Goal orientation connects students’ desired outcomes to the behaviors they engage in and the standards that they use to judge their performance, which in turn affect later performance [33]. Goal orientation theory originally described students’ goal orientations with two main categories - mastery and performance. Students with mastery goal orientations value learning and personal growth, whereas students with performance goal orientation value social demonstration of success and relative achievement. Pintrich and Schunk called these two goal orientations intrinsic and extrinsic, and these terms are used in the current study [44]. Prior research has consistently linked intrinsic motivation to academic achievement and extrinsic motivation to academic difficulties [62]. These results imply that an intrinsic goal orientation focused on mastery and learning is more conducive to academic success and needs be fostered in academic settings.

The initial goal orientation categories have been revised and refined as the theory has developed. Intrinsic goals remained the same, whereas extrinsic goals were divided into two subtypes, performance approach and performance avoidance goals [23, 19]. Performance approach goals are based on the desire for the appearance of success to others,
or success measured relative to others, whereas performance avoidance goals are based on the desire to avoid failure, particularly in view of others [34]. Empirical studies have shown a functional distinction between the two types of performance goals. Performance-approach goals predict adaptive behaviors in academic contexts, whereas performance-avoidance goals predict maladaptive behaviors [34].

2.1.3 Strategies for learning: Metacognitive strategies

Another important concept in self-regulated learning theory is metacognitive strategies. Metacognitive strategies are the self-monitoring and control processes used by students to select and implement appropriate behaviors to address an academic challenge [17]. Such strategies include, for example, asking oneself questions to check comprehension, or setting specific goals when studying. These strategies are a necessary component in the larger process by which self-regulated learning leads to increased academic outcomes [61]. Metacognitive strategies are important because they mediate between cognitive strategies and academic performance. Whereas cognitive strategies are the strategies employed to complete a specific task that are connected to the substantive content of that particular task, metacognitive strategies are more general strategies that involve awareness and executive control of the cognitive strategies. Previous research has found that students might use the appropriate cognitive strategies, yet still fail to successfully perform the task because they fail to appropriately use metacognitive strategies [17, 21].

2.1.4 Relationships between Constructs

Previous research has also shed light on the relationships between these different self-regulated learning constructs. For example, self-efficacy has been found to be positively associated with the use of more metacognitive strategies [42]. Similarly, intrinsic goal orientations have been shown to be positively associated with self-efficacy, whereas extrinsic goal orientations are negatively associated with self-efficacy [62]. Metacognitive strategy use has also been found to be significantly related to later self-efficacy, possibly mediated by the effects of performance on self-efficacy [1]. When considering all three constructs, a meta-analysis by Crede and Phillips found that self-efficacy consistently has the strongest relationship with academic outcomes, followed by metacognitive strategies and then goal orientation [18]. These previous results provided the basis for the model of the relationships between these constructs used in the present study.

Self-efficacy is unique among the SRL concepts being examined in this study because of its malleability and reciprocal relationships with learning outcomes [22, 36]. Initial self-efficacy beliefs affect performance, which in turn affects later self-efficacy beliefs. Bandura argued that self-efficacy should be assessed at significant points in a learning process in order to explain how this self-efficacy feedback loop functions in a given academic setting [4]. Previous research shows that the reciprocal effects of self-efficacy and performance lead to a correction of self-efficacy beliefs over time. As students have more opportunities for self-evaluation, the correspondence between self-efficacy beliefs and performance becomes greater [50]. In other words, students’ beliefs about what they can do become more accurate through feedback.

2.1.5 In CS Education

Previous research in computer science education has examined the individual relationships between the SRL constructs examined in this study (self-efficacy, achievement goals, and metacognitive strategies) and student learning outcomes in CS courses. Self-efficacy has been studied the most, with previous studies mostly confirming that self-efficacy predicts performance in CS contexts as it does in other academic settings. Ramalingam et al. found that students’ self-efficacy was positively associated with course grades and previous experience, and that it increased over time [46]. Wiedenbeck found that self-efficacy was positively associated with overall course grade and outcomes on a debugging task [58]. Wilson and Shrock unexpectedly found that self-efficacy was not significantly related to course midterm grades [60]. Watson and Godwin found that self-efficacy was by far the strongest predictor of performance in CS1, above many other predictors of success [56]. A qualitative study by Kinnunen and Simon found that self-efficacy judgments are continually evolving during the process of working on programming assignments in CS1, that positive and negative self-efficacy judgments are possible in response to both positive and negative results in programming, and that task difficulty and achievement goal orientation are possible moderators of these changes [28]. A precursor to this study found that programming assignments tend to catch students off guard with difficulties when they think that they understand what they are doing. These "struck by lightning" experiences produce particularly intense emotional reactions in students which have accordingly larger effects on students’ revisions to their self-efficacy beliefs [27]. These observations fit with the concept of the self-efficacy feedback loop, and suggest that this reciprocal process is worth further investigation in the context of students learning to program.

Goal orientations have been studied in CS classes multiple times as well, with the existing studies focusing on positive correlations between intrinsic goal orientations and grades. For example, Bergin and Reilly found that intrinsic goal orientations were associated with higher exam scores in a CS1 course [8], as did Zingaro and Porter [65]. Metacognitive strategies have been studied in CS as well, with observed results matching theory-based expectations. Bergin, Reilly, and Traynor found that the use of metacognitive strategies was associated both with intrinsic goal orientations and higher course grades in CS1 [9]. A qualitative study of students in an object oriented programming course showed that failures of metacognitive control accounted for problem solving failures [25]. Another qualitative study detailed the CS-specific and general types of metacognitive strategies used by introductory programming students [20]. These results confirm the importance of self-regulated learning constructs in explaining performance in introductory programming, with most of the findings aligning with previous research on precursors for success in other content areas [24]. Overall, studies of SRL constructs in CS have largely confirmed theoretically expected associations between these variables in the CS context, which supports the use of this theory to explain student outcomes in CS classes.

2.1.6 SRL and Gender in CS

The gender participation gap in CS has been widely noted and researched (see for example [49, 29, 54]). Recent data has shown that men outnumber women in CS bachelor’s de-
2.2 Need for study

The previous research in CS education on the motivational precursors for success has confirmed the importance of motivational and SRL constructs in introductory programming courses [25, 56, 65]. However, we still know little about the relationships between these factors and their influence on student outcomes. To date, no studies have looked at the relationships between self-efficacy, goal orientation, and metacognitive strategies in introductory programming courses. Previous studies from other disciplines have suggested relationships between these constructs, but it is unknown whether these relationships hold in the context of introductory programming.

In particular, the self-efficacy feedback loop has been little studied in CS. Kinnunen and Simón’s qualitative study suggested that something like a reciprocal self-efficacy feedback process occurs in introductory programming students, and the authors offered suggestions for keeping the feedback loop from becoming negative and driving students to failure [28]. The present study builds upon that study by further exploring the nature of the self-efficacy feedback loop in introductory programming by presenting the results of a larger quantitative study that also relates data on the self-efficacy feedback loop to other SRL constructs.

Another shortcoming of the previous work on motivation and CS is that programming performance has typically been measured by single course grade or exam grade, with little discussion or attention given to the implications of the choice of outcome measure. As has been argued elsewhere, different sorts of programming assignments appear to assess qualitatively different aspects of students’ learning in introductory programming courses [32]. For this reason, this study takes a multiple outcome measures approach to examining motivation-performance relationships, by using multiple indicators of programming performance. Furthermore, previous studies on motivational variables have only measured them at one time point rather than examining student trajectories over time. This study used repeated measures of self-efficacy to enable a finer-grained examination of the reciprocal self-efficacy-performance relationship.

While previous research has suggested the importance of affective processes in explaining gender differences, the reciprocal interaction between self-efficacy and learning outcomes in CS, as mediated by gender, has not been previously examined. The gender gap in CS is a significant issue, and a full understanding of it needs to include an examination of the gender-specific ways that the self-efficacy feedback loop operates and influences student learning. Hence, this study presents results on the gender differences in the nature of the self-efficacy feedback loop in introductory programming courses.

3. METHODS

3.1 Participants and Setting

This study investigated the relationships between SRL constructs and student performance on a sample of 346 students in a CS1 course at a large midwestern university. Of these students, 248 (73.1%) were male, 93 (26.9%) were female and 5 were unidentified. The class was taught by the fourth author of this paper, but he was not involved in the data collection and analysis process. The course was taught in a mostly flipped format; students watched video lectures and attended lab sessions with a TA in which they completed lab exercises.

3.2 Self-Regulated Learning Measures

The motivational and self-regulated learning constructs were measured using subscales from the Motivated Strategies for Learning Questionnaire (MSLQ). The MSLQ is a widely used self-report instrument designed to measure student motivation and learning strategies [41]. The MSLQ comprises 81 Likert-scale items across 15 subscales, six of which are designed to measure dimensions of motivation, and nine of which are designed to measure learning strategies. The MSLQ has also been used previously in CS education research to examine the relationships between individual subscales and student outcomes (see for example: [6, 56, 9, 51]). Beyond CS education, the MSLQ has been used in hundreds of studies, and its validity and reliability have been well substantiated.

For this study, 4 of the 15 subscales were chosen to measure the theoretical constructs of interest discussed previously. The scales used were self-efficacy, metacognitive self-regulation, intrinsic goal orientation and extrinsic goal ori-
entation. Of note is the extrinsic goal orientation subscale. When the MSLQ was developed, the theory on goal orientations had not yet divided extrinsic goal orientations into performance-approach and performance-avoidance. The items that comprise the extrinsic goal orientation subscale on the MSLQ are all oriented towards assessing the performance-approach goal orientation. The scales chosen for this study have been found to predict student outcomes consistent with self-regulated learning theory [18].

3.3 Programming Performance Measures
The programming performance dimension was assessed using student grades on different types of assessment. Previous CS education studies have generally used the overall course grade or final exam grade as outcomes. Other previous research, however, has suggested that different sorts of course assessments can measure qualitatively different aspects of student ability [3, 30], and so choice of outcome measure can have significant effects on the validity and interpretation of study results. For this reason, this study used 2 different measures of student performance, programming projects and multiple choice exams. The programming projects involved students writing complete programs, whereas multiple choice exams involved students answering questions about syntax, and tracing small bits of code. By using both measures, we can get a more fine grained picture of how motivation and learning strategies affect student performance.

4. DATA COLLECTION AND ANALYSIS
For this study, students were given an online survey containing the self-efficacy (Self-Eff init.), metacognitive self-regulation (Metacog Str.), intrinsic goal orientation (Intrin G.O.), and extrinsic goal orientation (Extrin G.O.) subscales in the second week of the course. Programming projects were due weekly starting the second week of the course, with the exception of weeks with midterm exams, which were given weeks 6 & 11. Course grade data consists of 7 programming projects and 2 multiple choice exams. Additionally, the self-efficacy subscale of the MSLQ was given to students on two subsequent occasions, 1 week before each exam, in week 5 (Self-Eff. R1) and week 10 (Self-Eff. R2). The data collection timeline is shown in figure 1.

The data for this study was primarily analyzed with a path analysis model. Path analysis is a structural equation modeling technique that allows one to model the explanatory relationships, including mediating relationships, for a set of variables with complex interactions [47]. A path analysis model was fit to explain the observed direct and indirect relationships between the observed variables, based on theoretical expectations for these relationships. This type of analysis is appropriate because the relationships between the motivation and learning strategies constructs are theoretically and empirically well-grounded. The goal of this analysis is to build upon previous research, which has shown evidence for relationships between motivation, learning strategies and performance, and to provide a more fine grained model of these relationships in the particular context of CS1. Sample size was not large enough to enable separate path models to be fit by gender, so gender differences were analyzed by looking at individual correlation and correlation pattern differences between males and females, which were tested for significance. All analysis was done using R version 3.2.1 and the lavaan package [45, 48], and visualizations were produced using the ggplot2 and DiagrammeR packages [57, 52].

5. RESULTS

5.1 Descriptive Statistics
Descriptive statistics on the four MSLQ subscales, as well as the two self-efficacy repeated measurements and the course grades, are shown in table 1. Data was collected at multiple points and there was some attrition. The final data set was 218 students who provided complete data on all measures. The MSLQ items are on a 7 point Likert scale, and sum scores were used as overall scores for these constructs. The intrinsic and extrinsic goal orientation scales have a maximum possible score of 28, the self-efficacy scale has a maximum possible score of 56, and the meta-cognitive strategies scale has a maximum possible score of 96. Exam 1 was worth 100 points, exam 2 was worth 150 points, and the 7 projects were worth a total of 235 points.

<table>
<thead>
<tr>
<th>Table 1: Descriptive Statistics: MSLQ and Grade variables</th>
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<tr>
<td>vars</td>
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<tr>
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<tr>
<td>Metacog. Strat.</td>
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<td>Self Eff. Init.</td>
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<tr>
<td>Intrin G.O.</td>
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<tr>
<td>Extrin G.O.</td>
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<tr>
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<td>Exam2 pts</td>
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<td>Proj pts</td>
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<tr>
<td>Self Eff. R1</td>
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<td>Self Eff. R2</td>
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</table>

Gender differences on these variables were also calculated, and there were no significant differences by gender, with the exception of the initial self-efficacy measurement, on which females scored significantly lower than males (t = 2.92, p-value = 0.004).

5.2 Path Analysis
The path model used total exam scores and total project scores as outcomes, with the MSLQ variables as independent variables. In accordance with previous research, self-efficacy
was hypothesized to have the greatest direct effect on performance, with metacognitive strategies and goal orientation having an indirect effect on performance through their effect on self-efficacy. Self-efficacy was measured 3 times, so the effects of earlier self-efficacy on later self-efficacy was modeled as well, as was the effect of earlier performance on later self-efficacy. In keeping with previous theory, goal orientation was hypothesized to influence both outcomes directly and indirectly through an effect on self-efficacy. Metacognitive strategies was hypothesized to have direct effects only on projects scores, because the monitoring and reflecting processes involved in meta-cognitive strategies do not show strong relationships with overall grades [18].

The model parameter estimates are shown in table 2. Model fit was good ($\chi^2 = 1.439$, df = 2, $p = 0.487$; CFI = 1.000; RMSEA = 0.000, 90% CI = (0.00, 0.122)) [26]. Previous theory suggested that self-efficacy would produce the strongest direct effects, and that the other MSLQ scales would have largely indirect effects, and the model results are consistent with these expectations. For exam scores, the strongest direct effect was self-efficacy, in particular the second repeated measurement ($\beta = 1.215$, $p < 0.001$). Project scores were also significantly related but the magnitude of the effect was much smaller than that of self-efficacy ($\beta = 0.290$, $p < 0.001$). As expected, extrinsic goal orientation had a negative effect on exam performance, but this effect was not significant, nor was the effect of intrinsic goal orientation. Interestingly, the first repeated self-efficacy measure had a negative effect ($\beta = -0.594$, $p = 0.010$). These results suggest a self-efficacy correction, as performance feedback made later self-efficacy more accurate than earlier self-efficacy. The variance explained for exam scores was moderate ($R^2 = 0.351$).

For project scores the only significant direct effect was that of the first repeated measurement of self-efficacy ($\beta = 1.215$, $p < 0.001$). This effect was similar in magnitude to that of self-efficacy on exam scores. Both extrinsic and intrinsic goal orientations had negative effects, but these were not significant, nor was the positive effect of metacognitive strategies. The nonsignificant effect of initial self-efficacy once again suggests a self-efficacy correction effect. As students progressed and received feedback, their self-beliefs became more accurate with respect to their actual performance. The second repeated measure of self-efficacy was not included in the model because it was measured after all of the projects, but its correlation with total project scores was greater than that of the first measure, which further supports this interpretation because later self-efficacy was more closely related to performance after there were more opportunities for performance feedback. The variance explained for project scores was small ($R^2 = 0.094$).

The path coefficients for the two repeated measurements of self-efficacy reveal the indirect effects of the other MSLQ variables. The second repeated measurement of self-efficacy was understandably most strongly related to the first repeated measurement and the initial measurement of self-efficacy ($\beta = 0.502$, $p < 0.001$; $\beta = 0.252$, $p < 0.001$). The larger effect of the first repeated measurement supports the interpretation that while self-efficacy had some continuity between measures, a correction effect occurred over time. Metacognitive strategies had only an indirect effect on the second repeated measurement of self-efficacy, with a significant direct effect on the first measurement ($\beta = 0.173$, $p = 0.005$). The same is true for intrinsic motivation ($\beta = 0.405$, $p = 0.005$). Extrinsic motivation had the expected negative effect on the first repeated measurement of self-efficacy, but it was not significant. The path diagram with the insignificant paths removed is shown in figure 2.

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**Figure 2: Path Model: Significant paths**

Overall, the results of the path analysis were expected, because the best predictor of both performance indicators was a self-efficacy measurement. Another unsurprising, but interesting, aspect of the results of the path model is the difference in variance explained between the two outcome measures in terms of total variance explained. While 35.1% of the variance of the total exam score variance was explained by the MSLQ variables in the path model, only 9.4% of the variance of the project scores was explained by the MSLQ variables. Part of this difference is due to the fact that the second repeated measurement of self-efficacy was not used to predict project scores, because it was measured after all of the projects were completed. Adding this variable would increase the variance explained to 17.0%. Nevertheless, the difference is substantial. This difference may have to do with the standardized nature of the multiple choice tests versus the open-ended nature of programming projects, which makes the scores produced by the exam more reliable than project scores, and therefore easier to predict. Another possibility, however, is that projects and exams differ significantly in the self-regulatory processes that are in-
volved in completing them. Metacognitive strategies, for instance, may play more of a role in completing a programming project than an exam, because projects require more planning and troubleshooting. The most likely possibility is that the factors involved in programming project performance are more multifaceted than those involved in exam performance. More complex interactions between the MSLQ variables and other cognitive and/or affective variables are likely involved, but the data collected in this study is insufficient to determine this.

<table>
<thead>
<tr>
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<th>p-value</th>
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5.3 Gender differences

In addition to the results on the overall path analysis, there were significant differences in the self-efficacy feedback loop by gender. Unfortunately, the obtained sample sizes were not sufficient to fit separate path models by gender, so significant gender differences on correlation patterns are reported instead. Correlations between the self-efficacy and performance indicators show a consistently distinct pattern for males and females. The correlation matrix for the self-efficacy and performance measures (exam and project totals) for men and women are shown in table 3.

<table>
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<th>SE R2</th>
<th>Proj.</th>
<th>Exam</th>
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<td>SE R1</td>
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<td>1.00</td>
<td>0.78</td>
<td>0.30</td>
</tr>
<tr>
<td>SE R2</td>
<td>0.47</td>
<td>0.63</td>
<td>1.00</td>
<td>0.31</td>
</tr>
<tr>
<td>Proj. pts</td>
<td>0.20</td>
<td>0.31</td>
<td>0.48</td>
<td>1.00</td>
</tr>
<tr>
<td>Exam pts</td>
<td>0.17</td>
<td>0.17</td>
<td>0.47</td>
<td>0.62</td>
</tr>
</tbody>
</table>

Correlations between the initial self-efficacy measurement and exam and project outcomes were not significantly different between male and female students, and these correlations increased across subsequent self-efficacy measurements, for both groups. However, for the remaining two self-efficacy measurements a distinct pattern emerged. In the case of both the projects and exams, female self-efficacy-performance correlations increased between the initial self-efficacy measurement and the first repeated measurement. However, between the first and second repeated measurements of self-efficacy, the self-efficacy-performance correlation did not increase significantly. For males on the other hand, there were sharp, statistically significant increases in the self-efficacy/performance correlation between the first and second self-efficacy repeated measurements, for both projects and exams. These results are shown in figure 3.

Figure 3: Gender differences in Self-Efficacy correction effect

Hypothesis tests showed that the correlation changes for males between the first and second repeated measurements of self-efficacy were significant, whereas the corresponding change was not significant for females. As shown in the chart, the effect is more pronounced for the exam scores, where the male self-efficacy-exam correlation does not increase at all between the initial self-efficacy measurement and the first repeated measurement, but it sharply increased by the second repeated measurement. This difference is consistent with the result from the path analysis, which showed that self-efficacy better predicted exam scores than project scores. However, the project/SE R2 correlation was statistically significantly higher for males than females, by contrast with the exam/SE R2 correlation, which was the same for both groups.

Change scores between the 3 self-efficacy measurements were also calculated and correlations with outcomes were computed. These tell the same story as the self-efficacy-performance correlations. For females, the change in self-efficacy from the initial measurement to the first repeated measurement had a greater association with scores on projects and exams than the change from the first repeated measurement to the second repeated measurement. For males,
the exact opposite was true for each outcome. The first change in self-efficacy had a weak correlation with performance, but the second change in self-efficacy had a significantly larger correlation. This difference in correlation patterns may be explained by the fact that between the initial self-efficacy measurement and the first repeated self-efficacy measurement, several projects were completed which would provide self-efficacy feedback whereas the first exam did not take place until after the first repeated self-efficacy measurement.

These results suggest that a self-efficacy correction occurs for both males and females as they progress through the course, but that the correction happens more quickly for females. The female self-efficacy - performance correlation reaches its plateau before students have even taken the first exam. Males on the other hand, are modifying their self-beliefs in response to performance feedback at least until the second exam. In the case of exam scores, the correlation with self-efficacy does not change at all for males until after the first exam, whereas it shows a modest (not statistically significant) increase before the first exam for the project - self-efficacy correlation. In each case, there is a clear pattern that suggests that females stop modifying their self-efficacy beliefs in response to performance feedback before exam 1 whereas males modify their self-efficacy beliefs significantly after exam 1. The change score correlations likewise corroborated this pattern. Overall, the correlation patterns suggest that for males the self-efficacy correction process takes longer and requires more performance feedback than for females. The flip side then is that males are more responsive to feedback, as there is a larger window of time during which performance feedback will significantly change their self-efficacy beliefs.

6. DISCUSSION AND CONCLUSIONS

The results of the path analysis reveal interesting patterns about the way that students' self-efficacy beliefs can influence their course outcomes and vice versa. The path analysis model showed that self-efficacy was the most important predictor of students' outcomes, but the model also shows the reciprocal effects of performance on self-efficacy. The important thing to take from these results is not that self-efficacy influences students' outcomes in CS1. This finding is not surprising given that prior research in both CS and non-CS classes has reported similar results. The important thing to take from these results is that metacognitive strategies and goal orientation impact self-efficacy, which impacts performance, and then performance impacts self-efficacy, which then impacts performance again. This self-efficacy feedback loop is the reason why self-efficacy is so important for performance and why managing it throughout the learning process has great potential to improve student learning outcomes in programming.

The results of the analysis also show a very interesting pattern in how male and female students modify their self-efficacy beliefs differently in response to performance feedback. Female students respond to performance feedback early in the course, revising their self-efficacy beliefs earlier. The implication of this result is important. It suggests that responses to early failures in CS could be causing female students to disengage from CS. As Kinnunen and Simon showed, programming assignments are characterized by their propensity to catch novice students completely off guard with difficulties, and produce intense emotional reactions [27]. If female students are more prone to internalize these early failures by revising their self-efficacy beliefs, this may discourage them from continuing to engage with programming. The gender participation gap in CS is a very significant issue, and the results of this study may offer one piece of of the explanation of this gap. Female students did just as well as male students in this course by all indicators, but how that success is related to their self-beliefs is quite different. Understanding how the self-efficacy feedback loop operates differently could perhaps be used to modify pedagogical approaches to reduce the attrition rate of females in CS.

Another important result to notice is the disconnect between the programming project outcome and the exam outcome. Earlier work has shown that programming projects and multiple choice exams can assess fundamentally different things, so it is not particularly surprising that we see different results in the path analysis. The different results in the path analysis show that variables outside of the ones we looked at are more important for predicting project scores than exam scores. This could mean a few different things. Perhaps there is an distinct self-efficacy feedback loop for programming projects. There may be additional cognitive factors that affect the self-efficacy feedback loop, or perhaps more complex relationships between the cognitive and motivational processes that occur when students do programming projects. Future research should delve deeper into these connections and investigate more of these complex relationships.

Overall, these results reinforce the notion that self-efficacy beliefs are part of a reciprocal relationship with performance. The self-efficacy feedback loop is important to CS researchers and educators because self-efficacy, unlike metacognitive strategies and goal orientations, is very malleable. Self-efficacy interventions could offer a unique opportunity to improve student retention in CS, particularly for female students. Many cognitive and affective factors are known to be correlated with success in CS [7] but few are as malleable as self-efficacy. The potential for interventions to redirect the self-efficacy feedback loop is great, and targeted self-efficacy interventions could potentially help reduce the gender participation gap. Self-efficacy is very important for success, and a better understanding of how self-efficacy develops helps improve our understanding of how students learn CS. Self-efficacy is of course just one piece of the larger puzzle, but these results represent an important step in our understanding of that piece.

7. REFERENCES


