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CS1: Intrinsic Motivation, Self-Efficacy, and Effort

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Abstract. This research investigates university students' success in their first programming course (CS1) in relation to their motivation, mathematical ability, programming self-efficacy, and initial goal setting. To our knowledge, these constructs have not been measured in a single study before in the Finnish context. The selection of the constructs is in line with the statistical model that predicts student performance ("PreSS") (Quille and Bergin, 2018). The constructs are compared with various demographic and background variables, such as study major, prior programming experience, and average weekly working hours. Some of the main results of this study are as follows: (1) students generally entered with a high interest in programming and high motivation, but these factors did not increase during the course, i.e., interest in programming did not increase. (2) Having prior experience yielded higher initial programming self-efficacy, grade expectations, and spending less time on tasks, but not better grades (although worse neither). While these results can be seen as preliminary (and alarming in some parts), they give rise to future research for investigating possible expectation–performance gaps in CS1 and later CS studies. As our dataset accumulates, we also hope to be able to construct a valid success prediction model.

Keywords: CS1, interest, motivation.

1. Introduction

Transitioning from high school to university is a vulnerable phase in early adulthood, as students may resort to unfruitful coping strategies when faced with difficulties (Dyson and Renk, 2006). Avoidant coping strategies, such as neglecting the existence of difficulties, have been found to be linked with depressive symptomatology (Dyson and Renk, 2006). Moreover, self-efficacy, self-regulation, and procrastination may play a central role in how students are able to study. Learning to learn and adapting to the conventions of a discipline at the university level is required of students (Wingate, 2007), while poor early assessments may result in low confidence, with students questioning their capacity to perform (Lizzio and Wilson, 2013). Students have also raised the challenge of undertaking work and studying without interruptions (cf. procrastination) (Hämäläinen and Isomöttönen, 2019). Additionally, institutions may not react fruitfully to students' difficulties. For instance, Leese (2010) emphasized the need for well-planned supporting interventions in place of academics, wondering at the characteristics of a new student.

This study investigates how goal setting, motivations (including value attributions), and self-efficacy relate to students' efforts and performance on an introductory programming course (CS1). Additionally, motivation and self-efficacy were measured at the beginning and the end of the course. This allowed us to investigate how changes in these constructs were associated with goals, effort, and performance. Motivation and self-efficacy measures are also included in the Predict Student Success ("PreSS") model (Quille and Bergin, 2018). To our knowledge, these measures have not been researched in a single study before in the Finnish context; Pollari-Malmi *et al.* (2017) have studied CS1 students' competence beliefs concerning the transition to digital learning materials. Finally, an analysis of the effect of background factors (e.g., prior programming experience) on the constructs mentioned above was also included in this study. Given these several data analytical lenses, the research approach was exploratory.

CS1 course often takes place at the very beginning of university studies. Thus, it is meaningful to investigate CS1 experiences and students' success in tandem with factors related to transitioning from a more structured studying environment (i.e., high school) to an environment that necessitates a more self-regulated approach to studying. Indeed, motivation, self-efficacy, and self-regulation have gained a lot of attention in the CS1 research literature and seem to relate closely to the experience of students transitioning to university. Despite the relatively broad body of earlier work, we were motivated to report the results of our explorative study because they appeared to differ from related work. This concerns, for instance, how prior programming experience influences performance: we could not confirm the positive correlation reported by Ramalingam *et al.* (2004). Based on such observations, we sought to complement previous research by discussing differences across studies and by proposing focused future work topics that take into account the pedagogic contexts.

In a theoretical sense, this study was based on Tinto's theorization of study motivation (Tinto, 2017). We considered this theorization to reflect the more general, extensively cited conceptualization of intrinsic motivation in Self-Determination Theory (SDT) (Deci and Ryan, 1980; Ryan and Deci, 2000) and used Intrinsic Motivation inventory based on SDT for data collection. As Tinto's theorization included self-efficacy as the key determinant of study motivation, we decided to give it proper attention by employing New General Self-Efficacy Scale by Chen *et al.* (2001). Students' prior experience and goals were asked by adding questions to a pre-survey. Efforts were collected by prompting for work hours in digital learning materials.

Section 2 reviews the aspects of motivation that we deemed relevant to our study. Section 3 details data collection measures and how the research was performed. Results are presented in Section 4 and discussion follows in Section 5. The main conclusions and proposals for future work are stated in Section 6.

2. Research Background

2.1. *Motivation to Study*

Motivation is a multi-faceted construct that can be viewed from multiple perspectives, including developmental, economic, sociological, and psychological (Deci and Ryan, 2012; Franzese, 2013). Franzese (2013) was interested in how motivation compares with the concepts of motive and agency and addressed the meanings of these concepts across disciplines. Across varying perspectives and definitions, the author outlined that motivation was generally seen as the "underlying reason" for doing something, whereas motive was the more immediate, "specific reason" for action. Agency was noted to be generally regarded as a capacity for action. Regarding the relationship between motivation and agency, Franzese (2013) explained that to have an underlying reason (motivation) for something, one needs to experience a capacity (agency) to strive for that something. In discussing individual agency, Franzese (2013) reviewed many topics, including the search for authenticity, which at a cultural level referred to the following of identities (see references in pp. 306–308).

The view provided by Franzese (2013) appears fitting to how Tinto (2017) treated study motivation in relation to persistence. Tinto's theorization expected that students starting their studies possess at least some kind of motivation to make progress toward a degree (an "underlying reason" in our interpretation) although such goal setting was considered vulnerable and not similar (e.g., equally strong) among students. For motivation to persist, Tinto emphasized three attributes in the students' experiences: *self-efficacy*, *belongingness*, and *perceptions of curriculum*. The first is the well-known construct indicating how individuals perceive their capacities in a particular situation (Bandura, 1977). The second refers to whether a student experiences a connection with the institution, the teachers, and the peers. The third refers to how students perceive the contents of their studies. Tinto explained that the curriculum might appear unchallenging, irrelevant, or too complicated with a lack of support. We identify some affinity between the three attributes stressed by Tinto and what was raised from Franzese above, that is, the need to experience agency in relation to motivation. Additionally, Tinto's work highlights the beginning of university studies as critical in light of the three attributes (explicitly referring to the critical first year when discussing self-efficacy), which makes his theorization relevant for understanding students' performance during first-year programming courses.

We identify similarities between Tinto's theorization and the self-determination theory (SDT) by Deci and Ryan (Deci and Ryan, 1980; Ryan and Deci, 2000), and argue that this connection supports the use of inventories derived from SDT when investigating the first-year students' study motivation. As part of their theory, Ryan and Deci identified psychological needs relatedness, competence, and autonomy as the constituents of intrinsic motivation (Ryan and Deci, 2000). We see an affinity (1) between the perceived competence (SDT) and self-efficacy (Tinto), (2) between relatedness (SDT) and belongingness (Tinto), and (3) between autonomy (SDT) and the perceptions of curriculum

(Tinto). We note that Deci and Ryan (e.g., 2012, p. 417) considered their attributes inherent to integrative processes in human development, ones that do not require learning. However, these attributes (or human needs) were influenced by social environments (e.g., Deci and Ryan, 2012, p. 417), which complies with Tinto's note that institutions can influence the attributes in his theorization. Concerning Deci's and Ryan's attributes, researchers have pointed to the tension between autonomy and competence in a way that lack of competence (e.g., skills that are still developing with respect to the given task) can make autonomy challenging to manage and, therefore demotivating (Noll *et al.*, 2017; Isomöttönen *et al.*, 2019).

2.2. *Self-efficacy and Performance, and other Motivation-related Attributes*

Self-efficacy in relation to academic performance has received ample attention. Honicke and Broadbent (2016) reviewed 59 studies in any discipline. They noted the varying specificity regarding what *performance* had indicated in this context. It referred to completing tasks, achieving a particular exam or course grade, passing a course, or being successful in university studies. Across 53 (out of 59) studies that provided correlational data for a metaanalysis, they observed a moderate positive relationship ($r^+ = .33$, $p < 0.0001$) between academic self-efficacy and academic performance; higher levels of academic self-efficacy are more likely to result in higher levels of academic performance. They also studied factors that mediated or moderated this relationship. For instance, students with proper self-efficacy are academically successful due to their cognitive processing strategies and effort that support learning, or high self-efficacy can abate procrastination and thereby lead to good performance.

Studies in computing education have documented the key role of self-efficacy for student performance (Bergin and Reilly, 2005; Rogerson and Scott, 2010; Campbell *et al.*, 2016; Quille and Bergin, 2018; Tek *et al.*, 2018; Gorson and O'Rourke, 2020). Bergin and Reilly (2005) reported comfort level as one of the critical success factors in students' experiences. The comfort level was outlined as an "ease when asking and answering programming questions [...] and self-efficacy for programming" (p. 294). Rogerson and Scott (2010) referred to a "fear factor" in learning to program. They noticed that students related negative perceptions to programming, such as stress, anxiety, and nightmare. These negative perceptions were noted to affect attitude and motivation, possibly resulting in procrastination and avoidance that further add to the negative feelings. As for procrastination, Shaffer and Kazerouni (2021) summarized previous literature indicating that procrastination is more likely to occur when tasks are perceived as unlikely to succeed, when outcomes seem distant or uncertain, or when multiple decision-making points are involved. Campbell *et al.* (2016) identified a positive correlation between self-efficacy and performance for online learners but not for their flipped classroom students. Quille and Bergin (2018) re-validated Predict Student Success model in CS1 and found the model to be still accurate. Programming self-efficacy was one of the key factors in the model.

Recently, Gorson and O'Rourke (2020) reported that students negatively assessed themselves across many programming situations and that these negative evaluations reflected a low-self efficacy. One explanation these authors identified was that students do not yet have a clear view of professional programming practice and problem-solving processes, resulting in high expectations and low self-efficacy. Tek *et al.* (2018) studied the effect of programming self-efficacy and fixed versus growth mindset on students' effort and performance. The authors concluded that those who believe in improvable programming aptitude and have higher programming efficacy make a more significant effort and achieve better grades. Linking with this, Turner (2014) called attention to the development of higher education students' self-belief in order to support their employability. The key argument was that the conceptualization of self-belief should include the students' perceptions that aptitude can be improved and that such perceptions should be supported in the educational contexts that students encounter.

Relations between self-efficacy and students' expectations of final grades have also been found. In the study by Quille and Bergin (2018), programming self-efficacy and the self-reported expected end-of-module results had the highest accuracy (along with two other factors) in predicting student success early in CS1. Relatedly, Rountree *et al.* (2004) argued that the most important reason for a failure was that the student was *not* expecting an excellent final grade. They concluded that computer science tends to appear as a subject where it is necessary "to be aiming for mastery rather than merely aiming to pass" (Rountree *et al.*, 2004, p. 103).

The above highlighted the importance of self-efficacy for performance and referred to several related or influential attributes (e.g., fear, anxiety, procrastination, self-assessment, view of the discipline, self-theorization of aptitude, and student expectations). Yet other factors that correlate with programming self-efficacy include previous programming experience (Hasan, 2003; Ramalingam *et al.*, 2004; Askar and Davenport, 2009), gender (Askar and Davenport, 2009; Lishinski *et al.*, 2016), and sense of belonging (Veilleux *et al.*, 2013). Of these, Hasan (2003) reported that prior programming experiences support computer self-efficacy beliefs, which can then positively influence studying in computing fields. Ramalingam *et al.* (2004) reported that a student's self-efficacy is influenced by prior programming experience and increases as the student progresses in an introductory programming course. Therefore, performance was considered to be affected both by self-efficacy and the accumulated learning (mental model) that contributes to self-efficacy. Askar and Davenport (2009) observed prior programming experiences to correlate with self-efficacy, but also that prior computer usage, in general, had a clear impact.

Askar and Davenport (2009) reported that females judged their self-efficacy significantly lower than males in the context of introductory Java programming and discussed that this, conforming to previous research, also concerns gifted girls. A similar gender effect on self-efficacy was observed by Lishinski *et al.* (2016), with the addition that males appeared less frustrated with programming. Overall, Lishinski *et al.* (2016) summarized that gender differences were self-efficacy and interest differences and that initial self-efficacy and interest beliefs shape students' experiences during their subsequent studying on a course.

Veilleux *et al.* (2013) found that the sense of belonging contributed to students' view of improvable aptitude and concluded that supporting the sense of belonging can increase students' resilience—consider in connection to above notes on aptitude from Tek *et al.* (2018) and Turner (2014). On the other hand, Campbell *et al.* (2016) could not confirm a sense of community contributing to success in their course. In this study, a sense of community could be expected to be influential based on observed high activity in the discussion forum of the course.

Because our study incorporates both pre-and post-measures, it is also essential to acknowledge the literature noting that students' study motivation can fluctuate. As a background remark, Aivaloglou and Hermans (2019) found that school students' intrinsic and extrinsic motivation and prior programming experience strongly correlated with their self-efficacy and inclination towards a CS career. This linkage also shows in the study by Säde *et al.* (2019), which developed a scale for investigating motivations and perceptions that underlie students' choice of starting to study computer science. Intrinsic value, that studying CS is enjoyable, and utility, that studying CS is helpful for one's future, were the highest-ranked motivational factors. The highest-ranked perception factors were (i) satisfaction with the choice of specialty and salary and (ii) job security. We can compare the observations and attributes in these two studies with other kinds of results. Isomöttönen *et al.* (2020) investigated students' identity development and found that many students currently studying on a first programming course doubted or were uncertain of the direction of their lives. Furthermore, Jones *et al.* (2010) observed a decrease in several attributes (expectancy, interest, utility, self-efficacy, attainment, identification) during first-year engineering studies. They concluded that the more challenging study contents faced along with the transition from high school to college could cause the observed decreases in self-efficacy and other attributes. Additionally, Bargmann *et al.* (2021) recently reported that students' career decidedness might reduce when their perceptions do not match their expectations. It thus seems that students' initial experiences and expectations can change. We believe that in addition to the transitional reasons, differences in educational cultures should be looked into as a potential explanation.

3. Course, Measures, and Participants

3.1. *Course*

The empirical part of this study was carried out within the Programming I course ("CS1") at the University of Jyväskylä during Spring 2021. Our CS1 course (6 ECTS, 160 hours) uses C# language and a procedural paradigm. The learning objectives consist of variables and functions and other typical CS1 topics (Dale, 2005), such as selection, repetition, arrays, and information encapsulation. Course completion requires passing an exam, a sufficient number of completed exercises during each week, and a course project, which typically involves programming a game.

The game theme is used to encourage students to start working on projects early, to keep them motivated, and to provide quick feedback on their progress. From the very beginning, students create graphic programs, including drawing and moving shapes with realistic physics, among other things. Throughout the course, exercises related to game development are given every week. By the end of the course, students work on a final project that consists of creating a functional computer game, which requires a total of 30 hours of work. To facilitate the game development, we use the Jypeli programming library as a framework for game development.

The course mostly had computer science (CS) and information systems (IS) majors, but other students from different faculties also took it as a minor or a filler course. CS/IS students had to take the course as it was mandatory for them. In the Participants section, we give more details about the students who participated in the study. Due to the covid-19 pandemic, the course was held only online, with the same amount of instruction (lectures, one-to-one instruction) as the traditional version in previous years. However, the pass rate for this course (around 60%) was slightly lower than usual (around 65–75%). This could be due to covid-related reasons such as the online-only setting, and the fact that the course was offered three times during the academic year. Unfortunately, this study does not provide any evidence to support these assumptions.

We want to clarify that we did not alter the course in any way as part of our research; the CS1 course was conducted exactly as it had been done previously.

3.2. *Measures and Data Collection*

Four types of data were collected: (1) pre-test at the beginning of the course, (2) weekly self-reports of working hours, (3) final course grade, and (4) post-test.

Pre- and post-tests were nearly identical. The tests included the Intrinsic motivation inventory (IMI) (Ryan, 1982) and New General Self-Efficacy Scale (NGES) (Chen *et al.*, 2001); these scales are described below in more detail. The pre-test additionally included background and demographical items, such as the expectation of a final course grade and earlier programming experience. With both tests, respondents were rewarded with an extra point that nominally contributed to their final grade. The tests were implemented as online questionnaires in the course learning management system and were an optional part of the coursework.

The demographic/background items of the questionnaires are listed in Appendix A. Complete questionnaires are available upon request.

We used four of the seven subscales of IMI that were relevant to this study: Interest/Enjoyment, Perceived competence, Value, and Effort. The Interest/Enjoyment subscale is considered the self-report measure of intrinsic motivation, while Perceived competence relates to behavioral measures of intrinsic motivation. For example, the Interest/Enjoyment subscale included questions like "I enjoyed doing this activity very much." Value and Effort, in turn, are linked to self-regulation and intent of free-choice behavior, respectively. For instance, the Effort subscale included questions like "I tried very hard on this activity." IMI part of the tests consisted of 24 and NGES of eight questions. All these items used a 7-point Likert scale: "Strongly disagree", ..., "Strongly agree". In the pre-test, the questions were in the future tense (e.g., "I will put a lot of effort into this"), and in the post-test in the past tense (e.g., "I put a lot of effort into this").

We used the original wordings of the scales[1], and only added a short introductory paragraph specifying that the word "activity" in the questions refers to "studying/learning programming in general during this course."

Weekly working hours were collected by asking students to report the total hours they had spent on the coursework: attending lectures or feedback sessions, doing weekly assignments or the course project, reading the learning material, and doing any other course-related activities. The hours were reported in conjunction with submitting the weekly assignments. Again, reporting the working hours were optional, and respondents were rewarded with an extra point.

Final course grade was based on the exam score (best of three attempts). Completing weekly assignments gave additional points to the exam score.

All data, except the final course grade, were self-reported by the participants.

3.3. *Participants*

A total of 306 students enrolled in the course, out of which 234 completed the pre-test, and 120 completed the post-test. Among those, 93 students completed both the pre-and post-test. As a side note, 167 students passed the course, making the pass rate 55%. Thus, we consider the response rate for this research to be 93 / 167 = 56%. The study participants consisted of IS students (ca. 40%) and CS students (ca. 20%) who took the course as a part of their major studies, and minoring students, such as physics students (ca. 2%). Many participants were from other subjects or chose not to disclose their degree programs (ca. 30%).

4. Results

In this section, we will address several research questions relevant to this study. The research questions and the analyses conducted to answer those questions are depicted in Table 1.

We also note that in this section, we shortened the four Intrinsic Motivation subscales and the selected Self-Efficacy scale with the abbreviation "IM/SE". We chose to spell IM/SE variables (Interest, Effort, etc.) with a capital firstletter and other included variables (prior programming experience, grade expectations, final grade, average working hours) in all-lower-case.

[1] Intrinsic Motivation Inventory was downloaded from https://selfdeterminationtheory.org/intrinsic-motivation-inventory/

Table 1
Research foci and the conducted analyses related to the foci

Research foci	Conducted analysis/-es
Pre-post difference in motivation and self-efficacy	t-tests
Motivation's and self-efficacy's correlations with prior experience, working hours, and final grades	Correlation analyses
Initial motivation's and initial self-efficacy's correlations to grade expectations, final grades, and working hours	Classifications, t-tests, correlation analyses
Prior experience's correlations to grade expectations, working hours and final grades	Correlation analyses
Mathematics ability's correlation to grade expectations, final grades, programming experience and working hours	ANOVA

4.1. *Motivation and Self-efficacy, Pre vs. Post*

First, the mean differences in motivation and self-efficacy between the pre-and post-tests were investigated. Results of the t-tests are displayed in Table 2. A statistically significant difference was found in the Effort (IM3) ($\delta = -.20$; 95% CI $[-.39, -.01]$). The differences in other scales (IM1, IM2, IM4, SE) were not statistically significant. In other words, on average, there were no significant changes in the motivation subscales (apart from Effort) or programming self-efficacy from pre-to post-test. Particularly, we note that Self-efficacy and Interest did not change from pre-to post-test, and the decrease in Value ($\delta = -.18$) was almost significant. Further, while there was an increase in Perceived Competence, it was not statistically significant.

We remind, that the analyses were done on those respondents who filled both the pre-and post-test. Thus, the aforementioned result (as well as all the following results) reflect the experience of this particular group of students who worked their way through the course. Students who dropped out did not participate in the post-test. There were five students who eventually failed the final exam and therefore did not pass the course; these students potentially had a more negative overall experience. Inspecting the Motivation/grade and Self-efficacy/grade crosstabs, this indeed seemed to be the case. For instance, all students who failed the course had lower Effort values in the post-test than

Table 2
Paired samples t-tests for Interest & Motivation (IM) and Self-efficacy (SE) scales.
Variables were measured on a 7-point Likert scale from 1 to 7. * $p < 0.05$

	pre	post	diff	n	t	p (2-tailed)
Interest (IM1)	5.1	5.2	0.08	90	0.772	0.442
Perceived Competence (IM2)	4.1	4.3	0.21	89	1.691	0.094
Effort (IM3)	5.7	5.5	−0.20	92	−2.109*	0.038
Value (IM4)	6.0	9	−0.18	93	−1.988	0.050
Self-efficacy	5.2	5.2	−0.05	92	−0.570	0.570

in the pre-test. However, the count of the not-passed students in the analysis is so low that we do not believe it affected the analysis.

To verify the assumption of data normality with t-tests, we ran the Shapiro–Wilk test. The test suggested that IM2, IM3, IM4, and SE were not normally distributed. However, by inspecting Q–Q plots and histograms, we discovered that the distributions were roughly normal and included only a few outliers that probably skewed Shapiro–Wilk test. We concluded that the distributions were appropriate for t-tests.

4.2. *IM/SE Associations with Prior Experience, Working Hours, and Grades*

4.2.1. *Correlational Analyses*

Next, bivariate correlation analysis was conducted on IM/SE, grade expectations, final grade, prior programming experience, and average weekly working hours. Most of the correlations were not statistically significant (see Table 3). We highlight our key observations about the correlations that were statistically significant.

First, we examine the pre-test IM/SE correlations with the other variables (see “pre”row of each variable in Table 3). Grade expectations correlated moderately with Interest ($\rho = .388$), Effort ($\rho = .316$), and Value ($\rho = .342$). In other words, students with higher grade expectations tended to score higher IM scores. A moderate positive

Table 3

Correlations (Spearman’s rho, 2-tailed) between Interest and Self-efficacy scales and single observed variables. ** $p < 0.01$.* $p < 0.05$. Correlations with $p \geqslant 0.05$ are not printed (—). For example, in the first row (“Interest, enjoyment“), students with higher scores in interest/enjoyment in the pre-test, also tended to have higher grade expectations (0.388), thus the positive correlation. Moreover, the change in students interest/enjoyment from pre-to-post correlated negatively with grade expectations

		Grade expect.	Final grade	Prior exper.	Average hours
Interest, enjoyment	pre	0.388**	0.173*	0.133*	—
	post	—	0.428**	—	—
	diff	−0.281*	—	—	—
Perceived competence	pre	0.523**	0.153*	0.255**	−0.144*
	post	0.328**	0.501**	0.212*	—
	diff	—	0.327**	—	—
Effort	pre	0.316**	0.171*	—	0.303**
	post	—	0.404**	—	0.443**
	diff	—	0.430**	—	0.274**
Value	pre	0.342**	0.156*	0.139*	—
	post	—	0.280**	—	—
	diff	—	—	—	—
Self-efficacy	pre	0.175*	0.165*	—	—
	post	—	0.343**	—	—
	diff	—	0.244*	—	—

correlation existed between grade expectations and Perceived competence (ρ = .523). With the final grade and prior programming experience, pre-test IM/SE variables yielded only weak correlations. Finally, there was a weak negative correlation between average working hours and Perceived competence ($\rho = -.144$), and a moderate positive correlation between the hours and Effort (ρ = .303).

Next, we look at the post-test IM/SE correlations with the other variables (see "post"row of each variable in Table 3). Grade expectation correlated moderately with Perceived competence (ρ = .328). Final grade correlates moderately with Interest (ρ = 0.428), Perceived competence (ρ = .501), Effort (ρ = .404), and Self-efficacy (ρ = .343). Prior programming experience only correlated weakly with Perceived competence (ρ = .212). Finally, average hours correlated moderately with Effort (ρ = .443).

Lastly, we examined how IM/SE variables' pre-post *differences* correlate with other variables (see "diff"-row of each variable in Table 3). Grade expectations correlated negatively and moderately with Interest difference ($\rho = -.281$). In other words, students with higher grade expectations tended to lose interest from pre-test to post-test. Final grade correlated positively and moderately with Perceived competence (ρ = .327), Effort (ρ = .430), and weakly with Self-efficacy (ρ = .244). In other words, students with higher final grades tended to manifest an increase in these areas of IM/SE over time. Prior programming experience did not correlate with IM/SE pre/post differences. Finally, average hours correlated moderately with Effort (ρ = .274). Thus, students with a higher number of average hours tended to also have increased scores in Effort.

4.2.2. *High IM/SE vs Low IM/SE*

Next, we examine how IM/SE were associated with grade expectations, final grades, and working hours. We made distinct analyses for both the pre-test and post-test. In the pre-test, we compared the participants with IM/SE scores above the median to those with scores below the median. In the post-test, we compared the participants whose IM/SE scores increased from the pre-test to the post-test to those with decreased scores. Mean differences between groups were tested with t-tests. Homogeneities of variances were confirmed with Levene's test; for most comparisons, variances were equal. Tests that do not assume equal variances are noted. Here, we highlight the key results that were statistically significant.

Regarding the pre-test, the trend was that students with higher IM/SE scores had higher grade expectations. In addition, higher IM/SE scores in the pre-test were associated with higher final grades and higher average working hours throughout the course. To some extent, these associations to grade expectations, final grades, and working hours, applied to all five IM/SE scores. For example, students with a higher score in Perceived competence had higher grade expectations ($\bar{x} = 3.88$, on a scale from 1–5) than those with a lower score in Perceived competence ($\bar{x} = 3.21$; $\delta = .679$, $t = -5.656$, CI 95% $[-.915, -.442]$), $p < .001$. Similarly, a higher score in Perceived competence manifested as higher final grades ($\delta = 633$, $t = -2.373$, CI 95% $[-1.16, -.107]$, $p = 0.019$).

In other words, students who showed high Perceived competence in the pre-test, were more likely to expect higher grades and also to reach them. Likewise, higher Effort score yielded higher grade expectations ($\delta = .496$, $t = -3.989$, CI 95% $[-.741, -.251]$, $p < 0.001$), final grades ($\delta = .543$, $t = -2.024$, CI 95% $[-1.07, -.014]$, $p = 0.044$), and also average working hours ($\delta = 2.18$ hours, $t = -3.607$, CI 95% $[-3.38, -.990]$, $p < 0.001$). Similar mean differences also were found in Interest variable. Finally, students with a higher score in Self-efficacy had higher final grades ($\delta = .552$, $t = -2.065$, CI 95% $[-1.08, -.025]$, $p = 0.04$, equal variances not assumed), but in grade expectations and working hours, we did not find a statistically significant difference. All in all, higher IM/SE scores in the pretest seem to associate with higher grade expectations, final grades and average working hours.

Regarding the post-test, there were no significant differences in grade expectations or average hours between the increased/decreased IM/SE groups. In other words, there was no association between the initial grade expectations and the incline or decline in IM/SE scores. On the other hand, it did not show in average working hours whether students' Interest, Effort, Value, etc., scores had increased or decreased over time. Some IM/SE scores were associated with the final grade, however. For example, students with an increased score in Perceived competence had significantly higher final grades ($\delta = .810$, $t = -2.355$, CI 95% $[-1.494, -.127]$, $p = 0.021$). In other words, students who perceived that their competence increased over time were more likely to yield higher grades. Further, an increased Effort score did yield substantially higher final grades ($\delta = 1.381$, $t = -4.556$, CI 95% $[-1.983, -.778]$, $p < 0.001$, equal variances not assumed). Increased Effort score also showed a statistically almost significant difference in average working hours ($\delta = 1.574$, $t = -1.847$, CI 95% $[-3.268, .119]$, $p = 0.068$). Thus, students whose Effort subscale scores increased over time.

4.3. *On Prior Experience, Working Hours, and Grades*

We first investigated prior programming experience and how it is associated with grade expectations, working hours and final grades. We divided the respondents into two groups for the following analyses based on their earlier programming experience; the students with zero written lines of code and those with more than zero lines of code. Following this division, 50.4% have any programming experience before. Participants were beginners, overall; 83% had written 0–50 lines of code. The question about earlier programming experience has been in our pre-surveys for many years and the above-mentioned 83% is in line with the typical course intake.

There was a statistically significant positive correlation between prior programming experience and grade expectations (Spearman $\rho = .337$, $p < .01$). Median values of grade expectations were 3 (on a scale from 1/Poor to 5/Excellent) for those with no programming experience and 4 for those who had at least some existing programming experience. The distributions in the two groups differed significantly (Mann-Whitney

$U = 3942$, $p < .001$). Effect size ($r = 0.29$) can be interpreted as medium (Cohen, 1992). However, prior programming experience showed no statistically significant effect on final grade ($U = 5488$, $p = .378$). Homogeneities of variances were confirmed with Levene's test. Neither did prior programming experience correlate with initial self-efficacy.

Out of all students who filled in their weekly working hours at least once, the average was 11.9 hours per week. When counting out the drop-outs, the average was 12.5 hours ($Med = 12$, $SD = 5.9$). Average working hours correlated negatively and weakly with earlier programming experience ($\rho = -.148$, $p = .031$). Grade expectations did not correlate with working hours. Finally, working hours correlated positively and weakly with the final grade ($\rho = .246$, $p < .01$).

4.4. *Note on High School Mathematics Syllabus*

In the pre-test, we asked about students' maths syllabus taken in high school and matriculation examination grades. Responses were grouped into (1) intermediate, (2) advanced, and (3) not applicable/exam not taken. One way ANOVA revealed that neither grade expectations ($F = .718$, $p = .489$, df $= 2$), final grades ($F = 2.384$, $p = .094$), programming experience ($F = 2.172$, $p = .116$), or average working hours ($F = .297$, $p = .743$) were different for these groups. However, if we only consider groups 1 and 2 (who did take the mathematics matriculation exam), there was a statistically significant difference ($t = -2.088$, $p = .038$): Those who took advanced math achieved significantly better final grades ($\delta = .622$).

Association between the mathematics syllabus and the expected final grade was investigated with crosstabs. This association turned out not to be statistically significant. Similarly, the mathematics syllabus was not associated with earlier programming experience.

5. Discussion

In the following sections, we return to the traditional lowercase spelling of motivation and self-efficacy.

5.1. *Pre-post Comparisons of IM/SE*

Regarding the pre-post differences in intrinsic motivation and self-efficacy, the only statistically significant difference concerning the whole population was seen in effort (a sub-scale of intrinsic motivation), where we found a negative association. Thus, interest and self-efficacy did not generally seem to change dramatically during our CS1 course setting. In a study by Lishinski and Rosenberg (2021), they discovered that when students believed in their ability to do well in a computer science course and were interested in the subject, they tended to have higher interest levels and final scores in the course. We also found a weak connection between students' belief in their ability to do well and their final course scores through our own analysis. However, there are likely other factors that affect students' motivation and belief in their abilities that we didn't account for in our study.

From the teacher's perspective, seeing the negative change in effort is a little upsetting. We need to try and clarify the underlying reasons why effort declines during the course. We are unsure whether the reasons lie in our local course setting, e.g., structure, support and guidance, pedagogy, or teachers' unrealistic expectations (Luxton-Reilly, 2016, p. 286). Another reason why students might find programming difficult is that they think it requires a lot of work compared to the credits they receive for it. This is something students often mention in their feedback after the course. However, even though students found programming challenging, their scores on the pre-test were still pretty good. For example, the average score for how much effort they were willing to put in was 5.7 out of 7.

5.2. *Prior Programming Experience*

Students' prior programming showed how they treated their expectations towards final grades; even a small amount (ca. 50 lines) of coding experience can yield higher grade expectations. However, such a connection did not exist between prior experience and final grade. Ramalingam *et al.* (2004) argued that prior experience influences programming self-efficacy and that self-efficacy affects course performance. In other words,prior experience affects performance and is mediated by self-efficacy. Similarly, Hagan and Markham (2000) strongly argued that those who had prior experience in one or more programming languages performed significantly better than those with none. In our study, we did not find statistically significant associations between prior programming experience and final grade or self-efficacy, thus, directly contradicting those earlier studies. Moreover, our study suggests that having prior experience yielded higher grade expectations, spending less time on tasks, but not better grades (although not worse either). While it is hard to say the underlying reasons for sure, we speculate that students who have earlier programming experience might have false beliefs about their abilities (i.e., too high competence beliefs or expectations for final grade), which leads to investing less time in learning. While we would not necessarily call prior experience a "mental trap," it might be worth addressing in the classroom that if a student has written 50 lines of code beforehand, it does not automatically mean better end-of-course outcomes. A similar discussion was provided by Davis (2009), who suggested that high levels of academic self-efficacy may result in overconfidence and, in turn, less preparedness for the exam, therefore decreasing the course results.

5.3. *Associations Between IM/SE, Performance and Grades*

We found moderate to strong connections between students' initial interest and grade expectations, and between initial self-efficacy and grade expectations. Thus, students who felt interested or had high self-efficacy beliefs at the beginning of the course tended to expect higher grades. However, when we inspected how the interest and self-efficacy variables developed over time, the correlational association between these variables and final grades diminished radically. The decrease of interest and self-efficacy aligns with the findings by Jones *et al.* (2010), who found that university students' motivation and value-related beliefs decreased between the first and second semesters.

Effort and perceived competence (subscales of intrinsic interest) were the only variables correlating with the final grade. Notably, increased effort scores yielded a substantial difference in final grades (Spearman $\rho = .430$). Learning to program requires a lot of effort, and it isn't easy to learn unless one does the necessary work. There is earlier research evidence that few learners acknowledge beforehand that programming requires a lot of work and is time-intensive (Simon *et al.*, 2009). Our study suggests that students whose understanding of the necessary effort for learning programming increases as the course proceeds are in an advantageous position regarding final grades.

Petersen *et al.* (2016) found that struggling students sometimes experience a "wake-up call" and can thereby make an informed decision to persist. Further, the students who acknowledged they were about to fall behind, *and* understood the need to use new techniques for learning and the need to increase their efforts, completed the course more often. Even though the present study does not directly reassert this phenomenon, the association of increased effort scores and higher final scores suggest that this might be the case in our research.

Continuing on self-efficacy, an overwhelming amount of evidence relates self-efficacy to student outcomes and persistence (Lishinski and Rosenberg, 2021; Honicke and Broad-bent, 2016; Multon *et al.*, 1991). Our study joins that choir. Students with above-average self-efficacy beliefs at the beginning of the semester tended to perform better in final course grades than those with lower initial self-efficacy beliefs. We also found a similar association between initial interest and final grades. Further, higher initial effort beliefs yielded higher working hours during the course, indicating increased performance and persistence. This association contradicts Shell *et al.* (2016): in their study, only for students in an honors program entering motivational beliefs weakly predicted achievement and retention – though they used other instruments to assess motivation. Even though the changes in interest and self-efficacy pre- and post-course were small or non-existent in the population, our key takeaway here is that both initial intrinsic interest and self-efficacy views and beliefs do contribute to performance.

6. Conclusion

In this paper, we found that students' initial interest and self-efficacy beliefs in programming are at a high level initially. Comparing the pre-and post-test scores, there were no changes in interest and self-efficacy, except for effort, which declined slightly during the course.

We also found some significant associations between interest/self-efficacy beliefs and student demographics, weekly working hour habits, and earlier maths success. Below, we highlight some of the most important findings.

- Initial interest and self-efficacy beliefs related to CS1 grade expectations and final grades. However, the relation (correlation) to final grades was weak, while a bit stronger on grade expectations.
- The change in interest and self-efficacy beliefs over time correlated moderately with final grades. That is, students who gained interest and self-efficacy in programming tended to get higher final grades.
- Students with higher grade expectations (at the beginning of the course) tended to lose interest and enjoyment with time.
- A change in effort beliefs correlated positively with final grades. That is, students whose effort beliefs increased tended to get higher final grades.
- Prior programming experience was associated with higher grade expectations. However, experience showed no effect on the final grade; the students with prior experience spent less time on tasks.
- Students who had taken an advanced maths syllabus in high school performed better than students with an intermediate syllabus.

We are tempted to conclude that students' effort beliefs specifically are a key indicator for success in introductory programming and persistence in programming. We can not confirm causality, however, and therefore the topic still needs to be further researched with more data and various methods.

The interesting question for further research is the potential mental trap that we discussed: programming experience-based early competence beliefs complicating students' effort and results. Follow-up studies should attempt to verify this observation. Furthermore, the follow-up studies could examine (i) if this is a global phenomenon and (ii) whether the alleged mental trap is affected by other variables than prior programming experience, such as previous maths grades. In our study, it seemed that students who had advanced maths in high school yielded significantly better CS1 grades than students with intermediate maths. Additionally, conducting similar studies in CS2 and other later programming courses could shed light on how students' perceptions potentially fluctuate regarding this effect.

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Appendix A. Questionnaire

1. Age: (a) 16–20, (b) 21–24, (c) 25–30, (4) >30 years
2. Major subject: (a) Computer science, (b) Information systems, (c) Physics, (d) Mathematics, (e) Cognitive science, (f) Other, (g) Don't know or don't want to answer
3. Highest degree to date: (a) Basic education, (b) High school / upper secondary school, (c) Vocational school, (d) Polytechnic, (e) Bachelor, (f) Master, (g) Doctor, (h) Other, (i) Don't know or don't want to answer
4. Matriculation exam: Grades in... a) Mathematics (intermediate) b) Mathematics (advanced) c) Finnish / first language
5. Longest written program to date: (a) 0 lines (no experience), (b) 50 lines or less, (c) 500 lines or less, (d) 5000 lines or less, (e) longer, (f) Don't know or don't want to answer
6. I have participated in this course (times): (a) this is my first time, (b) 1 time before, (c) 2 times before, (d) more, (e) Don't know or don't want to answer
7. My target grade for this course: (a) 5, (b) 4, (c) 3, (d) 2, (e) 1, (f) Don't know or don't want to answer
8. I plan to complete the following degrees at the University of Jyväskylä (each degree Likert 1 (fully disagree) – 5 (fully agree)): a) Bachelor b) Master c) Doctor d) No degree, just separate courses
9. Identity questions (28 items), DIDS scale
10. Motivation questions (24 items), IMI scale
11. Self-efficacy questions (8 items), GSE scale