Self-Regulation in Accelerated Programming for Engineers Online Learning: Participation Patterns and Outcomes of a Forethought Intervention

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Abstract:

Accelerated online courses place strong demands on students' self-regulated learning, particularly in the areas of planning and time management. Grounded in Zimmerman's self-regulated learning framework, this study examined a forethought-focused self-regulation intervention implemented in a fully online introductory programming course for engineers offered during an accelerated Summer A term of approximately eight weeks at a large public university in the southeastern United States. The intervention consisted of short, guided reflection prompts completed at the start of each module, asking students to identify upcoming tasks, and outline a plan to work on the module. Students were encouraged to complete these reflections throughout the term, with extra credit awarded for sustained participation, the threshold for which was participation in both exams and response to over half of the weekly surveys.

Students completed a validated online self-regulation questionnaire at the beginning and end of the course. Results showed significant changes in several self-regulation dimensions over time, reflecting the increasing demands of the accelerated course structure. Although overall self-regulation levels were similar across participation groups at both time points, students who did not engage or only minimally engaged with the intervention showed declines on selected self-regulation scales. In contrast, students who consistently participated in the self-regulation activities generally maintained stable self-regulation scores across the semester. About half of the class engaged consistently with the intervention. These findings highlight the difficulty of sustaining self-regulated learning in compressed online courses and suggest that simple, forethought-focused self-regulation supports may help students maintain planning and time-management skills when course demands are high.

1. Introduction

Online courses are now a common feature of higher education, offering flexibility, accessibility, and expanded learning opportunities for students [1]. At public undergraduate institutions in the United States, a majority of students enroll in at least one online course, and a substantial portion complete their coursework fully online [2]. While these formats provide clear benefits, they also shift greater responsibility onto students to manage their time, plan their work, and sustain engagement with limited external structure, challenges that are especially pronounced in asynchronous settings ([3], [4]). These demands become even more intense in accelerated courses, such as summer terms, where students are expected to complete a full semester's workload in roughly half the time. In such compressed environments, difficulties with planning, time management, and help-seeking can quickly compound, making self-regulation a critical factor in students' ability to persist and succeed, particularly in introductory technical courses that require sustained practice and problem solving.

Self-regulated learning provides a useful framework for understanding how students navigate these challenges. Zimmerman's model emphasizes the forethought phase—goal setting, planning, and time management—as a foundation for effective learning, particularly in contexts that require sustained independent effort [5]. Prior research in online higher education has identified time management as one of the most significant obstacles students face [6] and has shown that planning is a key predictor of both achievement and satisfaction in online courses [6]. At the same time, self-regulation is closely aligned with engineering education, where learners routinely engage in iterative cycles of planning, implementation, and revision that mirror the self-regulatory process [7]. These processes are especially salient in introductory programming courses for engineers, where students must learn new computational concepts while simultaneously developing effective study and practice habits. Although self-regulation has been examined separately in online learning contexts and in engineering education, less is known about how forethought-focused self-regulation—particularly planning and time management—operates in accelerated online engineering courses. Addressing this gap, the present study investigates a structured, forethought-focused self-regulation intervention designed to support students' planning and time-management processes in a fully online, accelerated introductory programming course for engineers.

To examine the impact of a forethought-focused self-regulation intervention in an accelerated online engineering course, this study addresses the following research questions:

RQ1. To what extent did students engage with the self-regulation intervention, as measured by participation and completion of the self-regulation activities?

RQ2. Are there differences in exam performance between students who engaged in the self-regulation intervention and those who did not participate?

RQ3. (a) How do students' online self-regulation skills change from the beginning to the end of the course, and **(b)** do these changes differ between students who engaged in the self-regulation intervention and those who did not?

2. Zimmerman framework

Self-regulated learning (SRL) is closely related to, but distinct from, constructs such as self-regulation and metacognition, which are often used inconsistently in the literature ([9], as cited in [8]). Broadly, self-regulation refers to how individuals respond to and shape their environment, while metacognition involves awareness and evaluation of one's own cognitive processes. SRL situates these ideas within a learning context, framing learning as an active process of constructing meaning through the interaction of personal, behavioral, and environmental factors ([10], as cited in [8]). This perspective aligns with Bandura's concept of reciprocal determinism, in which learners both influence and are influenced by their learning environments ([11], as cited in [8]). In this study, we adopt SRL as the primary construct of interest, recognizing metacognitive processes as integral components of self-regulated learning, particularly in online environments where students must independently manage their learning activities.

To operationalize SRL, we draw on Zimmerman's phase model, which conceptualizes self-regulation as a cyclical process consisting of forethought, performance, and self-reflection phases ([12]; [13]). The present work focuses specifically on the forethought phase, as it plays a critical role in planning and time management—skills that are especially salient in accelerated online courses. During forethought, learners engage in task analysis, which includes goal setting and strategic planning, and form self-motivation beliefs related to self-efficacy, outcome expectations, and task interest [13]. Together, these processes shape how learners allocate time, select strategies, and initiate action. Forethought processes are foundational to effective regulation, as insufficient planning or unrealistic time estimates can undermine subsequent performance and lead to disengagement. By supporting learners in explicitly articulating what they need to accomplish, how they plan to work, and how they will manage their limited time, forethought-focused interventions have the potential to strengthen students' regulatory capacity and support more adaptive engagement across the self-regulation cycle.

3. Literature review

Prior research has consistently shown that self-regulatory capacities are closely related to academic performance across learning contexts. Self-efficacy, in particular, has been identified as a central component of self-regulation ([14]; [15]; [16]) and has been positively linked to academic performance in online learning environments [17]. Similarly, goal setting—a key self-regulatory strategy within Zimmerman's phase model of self-regulation ([9]; [10])—has been associated with higher academic achievement [18] and described as a driving force behind the effective use of self-regulatory strategies more broadly [19]. Together, these findings suggest that learners' ability to set goals, plan strategically, and believe in their capacity to succeed plays a meaningful role in shaping academic outcomes, particularly in learning environments that demand sustained independent effort.

Because self-regulation can act as a mediator between students and their academic performance, prior work has also examined factors that support or hinder the development and use of self-regulatory skills. Students with prior experience in online courses tend to report greater use of self-regulatory strategies, including planning and time management ([15]; [18]). In engineering education specifically, class standing and prior experience with complex programming tasks have been found to correlate positively with self-efficacy related to self-regulation [14]. At the same time, several studies highlight persistent challenges. Lawanto and Febrian found that senior engineering students often exhibited deficiencies in self-regulation during early stages of capstone design, particularly during problem definition, leading to flawed assumptions that negatively impacted project outcomes [20]. Poor regulation during early planning stages has similarly been linked to difficulties generating well-developed ideas and fully understanding complex engineering problems [7]. These findings underscore the importance of supporting self-regulation early and consistently, especially in contexts that involve complex, multi-stage tasks.

Beyond prior experience, students' beliefs about effort and learning also influence their willingness to engage in self-regulatory strategies. Students who perceive effort as undesirable or costly are less likely to invest effort or apply self-regulatory strategies during learning tasks

[19]. Among undergraduate engineering students, fixed beliefs about ability and skepticism toward self-regulatory strategies have been associated with reduced willingness to adapt learning approaches [19]. To address these challenges, researchers have advocated for embedding explicit instruction and scaffolding of self-regulatory strategies directly into course design [19]. Empirical evidence supports this approach.

For example, guided self-reflection prompts have been shown to increase students' engagement with feedback, a key but often underutilized resource in higher education [21]. Similarly, Manganello et al. demonstrated that a structured intervention targeting effort investment, time management, help-seeking, and self-evaluation led to significant improvements across all phases of the self-regulatory cycle in an undergraduate engineering course[22]. Collectively, this body of work suggests that well-designed, course-embedded interventions—particularly those emphasizing forethought processes such as goal setting and planning—hold promise for supporting self-regulation in demanding online and engineering learning environments.

4. Methods

4.1. Context and Participants

The study was conducted in a fully online undergraduate programming course for engineers at a large public university in the southeastern United States. Summer A courses, offered during the first part of the summer semester term, are delivered in an accelerated format, with approximately eight weeks of instruction covering material typically taught over a sixteen-week semester. The course included multiple weekly assignments (e.g., demos, labs, quizzes), making planning and time management particularly integral. Demos assignments consisted of short instructive videos and corresponding exercises delivered in a multi-page format. These assignments constituted most of the time that students allotted toward coursework, with each demo's assignment estimated to take around 3 hours to complete. Lab assignments consisted of a slightly shorter segment of applied practice, estimated to take 2 hours for total completion. Quizzes consisted of short, proctored coding practice questions. In addition to regular coursework, the course included two projects and two online exams, the latter administered with Honorlock for remote proctoring. All students enrolled in the course were invited to participate in the study.

4.2. Intervention

At the beginning of the semester, students completed an online self-regulation instrument (SRL-O) [23], to establish a baseline measure of their self-regulated learning skills. The same instrument was administered again at the end of the semester to examine changes over time (*see Table 2*). The course followed a highly structured, accelerated format in which two instructional modules were released each week. Module X was released on Mondays and Module Y on Thursdays. All assignments associated with Module X (e.g., demos, labs, quizzes) were due by Wednesday, while all assignments associated with Module Y were due by Sunday of the same week.

In addition, during summer 2025, the instructional team offered extra credit to students for their participation in some self-regulation surveys (*see Table 1*). Particularly, 1 point per survey over 1000 points that they can earn in the course were given to students who completed more than five reflections over the term. Particularly, 1 point per survey was awarded to students who completed more than five reflections over the term, with the course consisting of 1000 total points. To be considered a completed survey for a given module, students were required to submit the self-regulation survey both on the day the module opened and prior to submitting any other assignment for that module. This timing constraint was designed to ensure that survey responses reflected students' forethought processes—specifically planning and time management—rather than retrospective reflection on completed material. Importantly, students were not assessed on whether they followed or completed the plans they articulated; credit was awarded solely for survey completion, emphasizing engagement with the planning process rather than evaluating successful task outcomes.

4.3. **Survey Design and Mapping to SRL Phases**

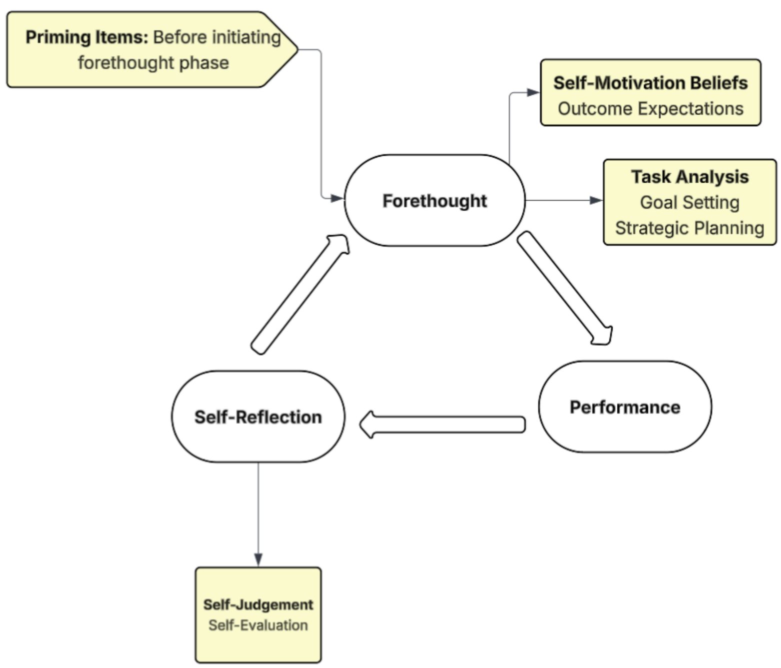

Figure 1 *Target Location of Survey Items in Zimmerman Phase Model:* Adapted from [4]. In the self-evaluation phase, students reflect on their experience with the module directly prior. In the forethought and performance phases, student responses refer to the current module.

Informed by previous literature, our current study investigates an intervention that would serve as a catalyst to help students implement self-regulatory strategies, particularly goal setting and strategic planning, during our online programming class. In the model presented in Figure 1, we designed survey items that honed in on two subcomponents of the forethought phase, task analysis and motivation beliefs, and the self-evaluative component of the self-reflection phase (see Figure 1). We also included several items that primed the forethought phase by encouraging students to consider and demonstrate accountability for their current progress, which was intended towards guiding their planning process for completing the array of virtual tasks assigned in the course.

The self-regulation survey consisted of a set of recurring questions administered during each module of the course. *Table 1* presents the mapping between survey questions and the targeted self-regulated learning phases and sub-phases. Forethought-focused items prompted students to articulate what they intended to learn, when they planned to complete specific assignments, and how they would allocate their time across tasks. Reflection-focused items encouraged students to evaluate their current standing in the course and consider their progress relative to their goals. Together, these items were designed to make planning and time management explicit and actionable on a weekly basis.

Table 1: **Survey questions mapped to the SRL phases and sub-phases using Zimmerman, B. J., & Moylan, A. R. (2009). Self-regulated learning and academic achievement: An overview. Educational Psychologist, 34(1), 7-20.**

Survey Question	**Target Construct**
What are you going to be learning in the current module?	Forethought Phase: Self-Motivation Beliefs, Outcome Expectations
Have you completed the demos assignment for the current module?	Priming items
Have you started the demos assignment for the current module?	Priming items
When do you plan to complete your demos assignment for the current module?	Forethought Phase: Task Analysis, Goal Setting
Have you completed the lab assignment for the current module?	Priming items
Have you started the lab assignment for the current module?	Priming items
When do you plan to complete the lab assignment for the current module?	Forethought Phase: Task Analysis, Goal Setting
Have you completed the quiz assignment for the current module?	Priming items
When do you plan to complete the quiz assignment for the current module?	Forethought Phase: Task Analysis, Goal Setting
Are there any other assignments you need to complete? If so, what is your plan to work on them?	Forethought Phase: Task Analysis; Goal Setting, Strategic Planning

How are you feeling about where things are in the course right now? Do you have any feedback or suggestions for the course? (Optional)	Self-Reflection Phase: Self-Judgment, Self-Evaluation This survey question does not directly target a specific construct, but students may draw on self-efficacy to determine how effectively the course supports their learning goals.

4.4. Online Self-Regulated Learning Instrument

To measure students' self-regulation skills more broadly, we administered the Self-Regulation for Learning Online (SRL-O) [23] questionnaire at the beginning and end of the course. The SRL-O is a validated self-report instrument specifically designed for online and blended learning contexts. It consists of 44 items measured on a 7-point Likert scale and captures ten dimensions of online self-regulated learning, encompassing both motivational beliefs and learning strategies. Motivational belief scales include online self-efficacy, online intrinsic motivation, online extrinsic motivation, and online negative achievement emotion, while learning strategy scales include planning and time management, metacognition, study environment, effort regulation, social support, and task strategies. Prior validation studies using exploratory and confirmatory factor analyses have demonstrated strong psychometric properties and internal reliability across all scales [23]. In the present study, scale scores were used to examine changes in students' online self-regulation from the beginning to the end of the course, as well as differences between students who engaged with the self-regulation intervention and those who did not.

Table 2 **: SRL-O Scales and Number of Items per Scale**

Category	SRL-O Scale	Description	# Items
Motivational Beliefs	Online Self-Efficacy (OSE)	Confidence in ability to succeed and persist in online coursework	4
	Online Intrinsic Motivation (OIM)	Engagement driven by interest, enjoyment, and mastery	5
	Online Extrinsic Motivation (OEM)	Engagement driven by grades, rewards, or external evaluation	3
	Online Negative Achievement Emotion (ONAE)	Negative emotions such as anxiety, shame, boredom, or hopelessness	5
Learning Strategies	Planning and Time Management (PTM)	Goal setting, prioritization, and allocation of time for online study	5
	Metacognition (M)	Planning, monitoring, and evaluating one's learning processes	5
	Study Environment (SE)	Ability to manage a distraction-free study space	3
	Online Effort Regulation (OER)	Persistence and effort despite difficulty or distractions	4
	Online Social Support (OSS)	Willingness to seek help and collaborate online	5

Online Task Strategies (OTE)	Strategies for processing, organizing, and applying content	5
Total		**44**

4.5. Data Analysis

All analyses were conducted using Python [24], with pandas used for data manipulation [25], matplotlib [26], seaborn for visualization [27], and standard statistical libraries for inferential testing. Prior to analysis, the dataset was cleaned to include only students who completed both Exam 1 and Exam 2, to exclude students who may have withdrawn or stopped engaging with the course. In addition, only students who completed both the pre- and post-course self-regulation questionnaires were included in analyses involving self-regulated learning measures. Questionnaire data were further screened for straight-line responding behavior, and responses exhibiting this pattern were removed to improve data quality and ensure the reliability of self-reported measures.

For this study, students were classified into three groups:

(1) **No Participation:** Students who did not complete any module self-regulation surveys.
(2) **No Extra Credit:** Students who completed at least one survey but fewer than six, and therefore did not earn extra credit.
(3) **SRL Extra Credit:** Students who completed six or more surveys and earned extra credit.

RQ1: To what extent did students engage with the self-regulation intervention, as measured by participation and completion of the self-regulation activities?

To examine the extent to which students engaged with the self-regulation intervention, we computed descriptive statistics capturing survey completion frequency across the term. Participation distributions were visualized using bar charts and overall group statistics.

RQ2: Are there differences in exam performance between students who engaged in the self-regulation intervention and those who did not participate?

To evaluate differences in exam performance between students who earned extra credit through the self-regulation intervention (SRL Extra Credit) and those who did not participate (No Participation), we conducted independent-samples *t*-tests. Given unequal sample sizes and observed variance differences, homogeneity of variance was assessed prior to analysis, and Welch's *t*-test was used [28].

RQ3: (a) How do students' online self-regulation skills change from the beginning to the end of the course, and (b) do these changes differ between students who engaged in the self-regulation intervention and those who did not?

To address the research questions, subscale scores were first normalized to account for differing numbers of items. Specifically, each subscale was converted from a summed score to a per-item mean by dividing the total subscale score by the number of items, placing all subscales on a common 1–6 metric. Because the Online Negative Achievement Emotion (ONAE) subscale reflects maladaptive emotions, it was reverse-coded after normalization (7 − ONAE mean) so that higher values consistently reflected a more adaptive motivational profile.

Two higher-order composite scales were then computed at both pre- and post-test by averaging the relevant normalized subscale means. Motivational Beliefs was calculated as the mean of Online Self-Efficacy (OSE), Online Intrinsic Motivation (OIM), Online Extrinsic Motivation (OEM), and reversed ONAE. Learning Strategies was calculated as the mean of Planning and Time Management (PTM), Metacognition (M), Study Environment (SE), Online Effort Regulation (OER), Online Social Support (OSS), and Online Task Strategies (OTE).

Given the sample size (N = 80) and the risk of inflating Type I error due to multiple comparisons, inferential analyses were conducted at the level of the two higher-order composite scales rather than at the individual subscale level. Conducting separate statistical tests across all ten subscales would have substantially increased the number of comparisons and reduced statistical power. Therefore, subscale-level differences were not tested inferentially. Instead, a radar plot was generated to provide a descriptive visualization of multidimensional pre–post patterns across subscales.

To examine overall change across the semester, paired-samples *t*-tests were conducted comparing pre- and post-test scores on each composite scale for the full sample. To further investigate whether change differed by intervention engagement, paired-samples *t*-tests were conducted separately within each participation group (No Participation, No Extra Credit, and SRL Extra Credit) for both composite scales. Effect sizes were calculated using Cohen's *d* for paired samples (mean difference divided by the standard deviation of the difference scores) to quantify the magnitude of pre–post change within each group.

5. Results

During Summer 2025 this programming for engineers' course had a total of 110 students enrolled, 80 of those students participated in both exams and responded to SRL-O instruments. The present analysis is performed using those 80 students.

5.1. RQ1: Participation in the Self-Regulation Intervention

A group corresponding to 60% of the students analyzed participated regularly, with many completing most of the weekly surveys (SRL Extra Credit, n = 48), suggesting sustained engagement throughout the semester. At the same time, a sizable portion of the class showed less engagement (No Extra Credit, n = 10), including 22 students who never completed a survey (No participation, n = 22). *Figure 2* shows how often students participated in the weekly self-regulation surveys across the course. Overall, engagement was mixed and clearly split between students who used the intervention consistently and those who did not engage at all.

For students who did participate, engagement appeared intentional rather than superficial. The average time spent on each survey was about 3 minutes, indicating that students were likely reading and responding thoughtfully rather than clicking through quickly.

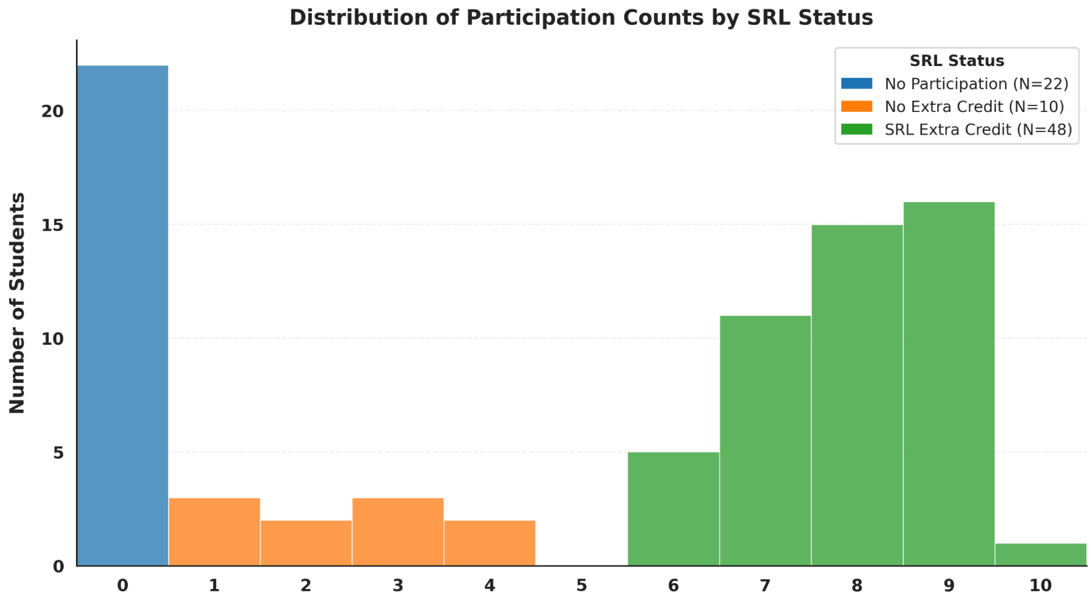

Figure 2: Distribution of student participation in weekly self regulation surveys across the course, showing the number of surveys completed by each student.

5.2. RQ2: Exam Performance Differences

Table 3 presents the distribution of EXAM 1 and EXAM 2 scores across the three groups: (1) No Participation (students who did not complete any module self-regulation surveys), (2) No Extra Credit (students who completed at least one survey but fewer than six and therefore did not earn extra credit), and (3) SRL Extra Credit (students who completed six or more surveys and earned extra credit). Overall, group differences were more evident in score dispersion than in mean performance. Across both exams, the No Participation and No Extra Credit groups demonstrated tightly clustered, high scores with limited variability, whereas the SRL Extra Credit group exhibited greater dispersion, particularly on Exam 2 (*see Table 3*).

Independent-samples *t*-tests comparing the SRL Extra Credit and No Participation groups indicated no statistically significant differences in mean performance for Exam 1, $t(53) = 0.54$, $p = .59$, or Exam 2, $t(67) = 1.60$, $p = .11$. These findings suggest that although variability differed across groups, mean exam performance did not significantly differ at conventional significance levels.

Table 3. Descriptive statistics for Exam 1 and Exam 2 scores by self-regulated learning (SRL) participation status

SRL Status	Exam	N	Mean	SD	P15	Median	Min	Max
No Participation	Exam 1	22	169.36	2.98	170	170	156	170
No Extra Credit	Exam 1	10	170	0	170	170	170	170

SRL Extra Credit	Exam 1	48	168.9	3.97	170	170	149	170
No Participation	Exam 2	22	164.95	13.09	170	170	127	170
No Extra Credit	Exam 2	10	170	0	170	170	170	170
SRL Extra Credit	Exam 2	48	155.98	33.55	136	170	0	170

5.3. RQ3: Changes in Online Self-Regulation

To address research question (a)—how students' online self-regulation skills changed from the beginning to the end of the course—paired-samples *t*-tests were conducted on the two composite scales. As shown in Figure 3, both Motivational Beliefs and Learning Strategies declined from pre- to post-test. However, the magnitude of change differed substantially between the two constructs. For Motivational Beliefs, the observed decreases were small and statistically non-significant, with negligible-to-small effect sizes, suggesting that students' confidence, intrinsic interest, external motivation, and emotional orientation toward online learning remained relatively stable across the semester (*see Figure 3*, left panel). In contrast, Learning Strategies showed statistically significant declines from pre- to post-test, with meaningful effect sizes (*see Figure 3*, right panel), indicating a reduction in students' reported use of planning, metacognitive monitoring, effort regulation, environmental management, social support seeking, and task strategies over time.

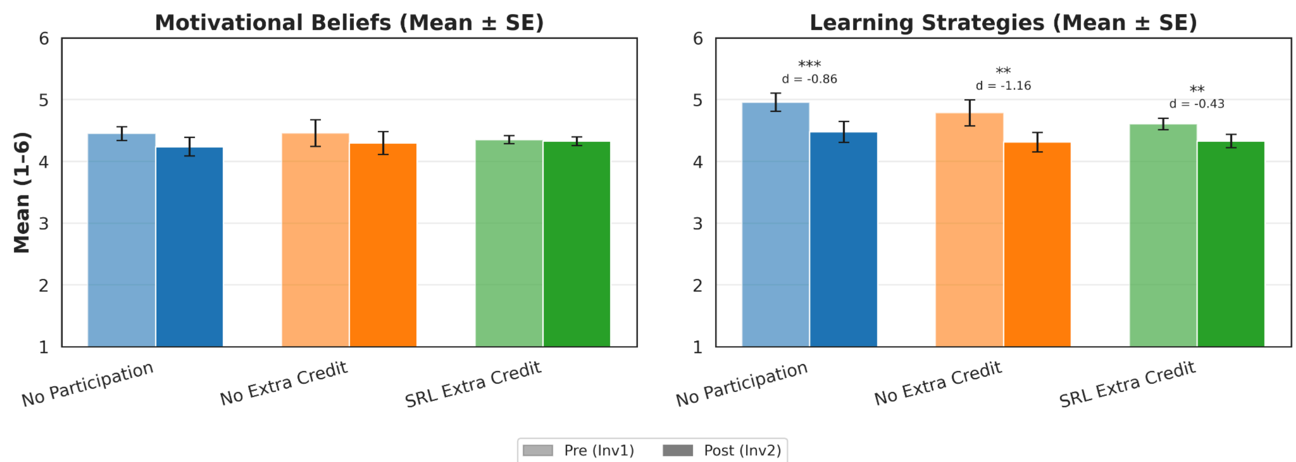

Figure 3: Pre- and post-semester mean scores (± SE) for Motivational Beliefs and Learning Strategies by participation group. Stars indicate statistically significant paired pre–post differences within groups ($p < .05$, *$p < .01$, **$p < .001$). Effect sizes are reported as Cohen's *d* for paired samples.

Descriptively, the radar plots in *Figure 4* help make the pattern of change more intuitive. Across all three groups, the post-test profiles, shown with solid lines, tend to sit slightly inside the pre-test profiles, shown with dashed lines, particularly for the Learning Strategies subscales. This visual contraction is most noticeable around Planning and Time Management (PTM), Metacognition (M), and Online Task Strategies (OTE), suggesting that these areas may be driving much of the overall decline in Learning Strategies observed in the statistical analyses. In contrast, the Motivational Beliefs subscales, including OSE, OIM, OEM, and reversed ONAE, appear relatively stable, with only small shifts from pre to post. The SRL Extra Credit group shows the smallest gap between the dashed and solid lines across many dimensions, especially within the Learning Strategies cluster, which aligns with the smaller effect size found in the inferential results. Because radar plots can present interpretability challenges, particularly when comparing multiple dimensions simultaneously, a full statistical table with descriptive values for all subscales is provided in Appendix A for readers who would like a more detailed numerical breakdown.

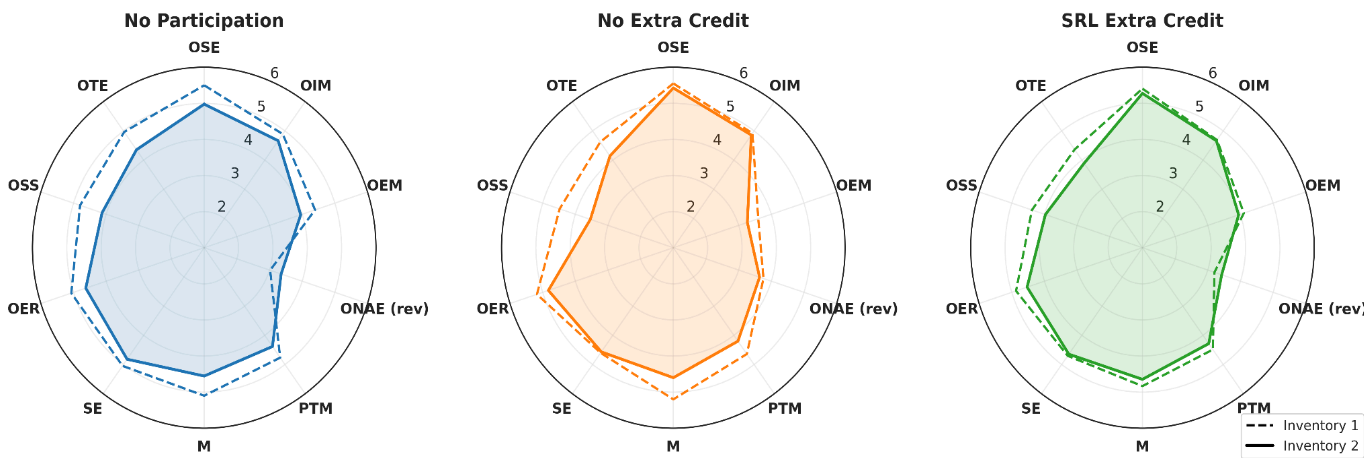

***Figure* 4.** Mean SRL-O [23] subscale scores at pre-course (Inventory 1) and post-course (Inventory 2) for students with no participation, limited participation (Not SRL), and sustained engagement (SRL) in the self-regulation intervention.

6. Discussion

This study aimed to understand how students’ online self-regulation changed over the course of a short, intensive class and whether a very simple intervention—a short three-minute self-regulation survey at the beginning of each module—made any difference. A few patterns stand out.

First, students participated in the intervention even when the extra credit attached to it was relatively small. That is meaningful. It suggests that even a light incentive can encourage students to engage in brief structured reflection about how they are approaching their learning. From an instructional design perspective, this is encouraging. It means that a short, low-burden activity embedded at the beginning of each module can generate consistent participation without needing to significantly alter grading policies or course structure.

Second, we did not observe differences in exam performance across participation groups. Importantly, this does not necessarily mean the intervention had no value. It is possible that students who completed the full extra credit component were those who felt they needed the additional points rather than those who were already strategically strong. In that sense, participation may have been driven by grade-related necessity. If students who were more concerned about their performance were more likely to complete the surveys, the absence of exam score differences becomes less surprising. It also reinforces the idea that shifts in how students perceive and regulate their learning may not immediately translate into measurable performance gains—particularly in a compressed, high-demand course. Learning processes and exam outcomes do not always move in parallel.

Third, the general decline in Learning Strategies across all groups is striking and deserves careful reflection. While Motivational Beliefs remained relatively stable, students reported lower use of planning, monitoring, and task-related strategies by the end of the semester. This finding is consistent with prior work suggesting that self-regulation can erode under sustained cognitive and temporal demands if not actively supported ([20]; [7]). The accelerated Summer A format—in which students completed a full semester's workload in approximately eight weeks, often with overlapping module deadlines—likely intensified these pressures. Within this context, the self-regulation survey did not appear to elevate self-regulation above baseline levels, but rather to function as a form of scaffolding that helped students sustain their regulatory practices over time. This pattern echoes prior evidence that embedded, low-stakes self-regulatory supports can help students persist through demanding learning tasks by reinforcing planning and time-management behaviors ([19]; [22]).

An additional and noteworthy possibility is that students may overestimate their self-regulation abilities at the beginning of an accelerated online course. Students entered the course reporting relatively high levels of self-regulation across several SRL-O subscales, yet declines were observed over time, particularly among those who did not engage with the intervention. This pattern suggests a potential miscalibration between students' initial perceptions of their planning, time management, and task strategies and the realities of navigating an intensive, fast-paced online programming course. Prior research has documented similar overconfidence effects, especially among learners with limited experience in complex or time-compressed environments [19]. In this sense, the observed declines may reflect not only erosion of strategy use, but also recalibration—students adjusting their self-assessments after encountering authentic performance demands.

Importantly, although all groups showed declines in Learning Strategies, the decline was smaller for students who earned the SRL extra credit. The effect size for this group was small, compared to large declines in the other two groups. This does not suggest that the short survey eliminated the downward trend, but it may have softened it. Descriptively, task-related strategies appeared more stable in the extra credit group. While modest, this pattern is promising. A brief three-minute survey at the beginning of each module is a minimal intervention, yet it may help buffer against sharper declines in perceived strategy use during demanding academic periods.

7. Limitations

Some limitations should be considered when interpreting the findings of this study. First, participation in the self-regulation intervention was voluntary and incentivized through extra credit, which may have introduced self-selection effects and limited causal inferences about the impact of the intervention. Second, self-regulation was measured using self-report instruments, which are subject to response biases and may reflect students' perceptions rather than their enacted regulatory behaviors. Second, placement in the self-regulation group was contingent on engagement with a self-report instrument, which is subject to response biases and may reflect students' perceptions rather than their enacted regulatory behaviors. It is also difficult to determine an objective standard for effortful completion of the survey instrument. Third, the study was conducted within a single accelerated online programming course at one institution, which may limit the generalizability of the findings to other disciplines, institutions, or instructional formats.

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Appendix A:

	Overall	Overall	NP	NP	NEC	NEC	SRL EC	SRL EC
	Pre	**Post**	**Pre**	**Post**	**Pre**	**Post**	**Pre**	**Post**
n	80	80	22	22	10	10	48	48
Motivational Beliefs	4.39 (0.50)	4.30 (0.55)	4.45 (0.51)	4.24 (0.71)	4.46 (0.68)	4.30 (0.58)	4.35 (0.46)	4.33 (0.47)
Learning Strategies	4.73 (0.67)	4.37 (0.73)	4.96 (0.69)	4.48 (0.79)	4.79 (0.66)	4.31 (0.49)	4.61 (0.65)	4.33 (0.75)
OSE	5.45 (0.61)	5.21 (0.85)	5.50 (0.60)	4.98 (1.27)	5.55 (0.70)	5.42 (0.39)	5.41 (0.60)	5.28 (0.65)
OIM	4.78 (0.75)	4.69 (0.91)	4.89 (0.89)	4.66 (1.18)	4.92 (0.73)	4.86 (0.49)	4.69 (0.68)	4.66 (0.84)
OEM	4.12 (1.17)	3.86 (1.14)	4.39 (1.31)	3.95 (1.00)	3.60 (1.18)	3.27 (1.24)	4.10 (1.09)	3.94 (1.16)
ONAE (rev)	3.22 (0.94)	3.43 (1.01)	3.02 (0.79)	3.35 (1.06)	3.76 (1.77)	3.64 (1.40)	3.20 (0.73)	3.42 (0.91)
PTM	4.58 (0.88)	4.30 (1.06)	4.76 (0.95)	4.38 (0.94)	4.64 (0.64)	4.20 (1.01)	4.49 (0.90)	4.28 (1.14)
M	4.95 (0.81)	4.62 (0.90)	5.10 (0.94)	4.55 (0.94)	5.20 (0.68)	4.60 (0.75)	4.83 (0.76)	4.65 (0.93)
SE	4.78 (0.84)	4.68 (0.99)	5.05 (0.74)	4.82 (1.09)	4.60 (1.09)	4.57 (1.08)	4.70 (0.82)	4.65 (0.93)
OER	4.96 (0.74)	4.59 (0.95)	5.07 (0.65)	4.62 (0.93)	5.17 (0.79)	4.83 (0.72)	4.87 (0.77)	4.53 (1.01)
OSS	4.51 (0.97)	3.96 (1.11)	4.80 (1.12)	4.13 (1.34)	4.48 (0.75)	3.54 (0.99)	4.38 (0.93)	3.97 (1.02)
OTE	4.56 (0.88)	4.05 (0.92)	4.96 (0.84)	4.35 (1.00)	4.62 (0.92)	4.14 (0.53)	4.36 (0.84)	3.89 (0.92)