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Engagement with Metacognition-promoting Web-based Interventions and its Relationship with Learning Outcomes

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Abstract

Metacognition—commonly referred to as ”thinking about thinking”—has been consistently linked to improved learning strategies and student achievement. However, no prior literature has practiced an intervention that addresses all three phases of Zimmerman’s Cyclical Phases Model of metacognition while aiming to help students better understand concepts in computing. Therefore, using CompassX we include 1) an initial *forethought* phase in which students plan their studying, 2) a *performance* phase in which students self-monitor their progress, and 3) a *self-reflection* phase where students evaluate and adjust their strategies. In this paper, we share the key features of CompassX that promote metacognitive study behaviors, how our users engaged with those features, and how continued practice of metacognition using those features is related to improved learning outcomes. Students used CompassX voluntarily and some students did not fully engage with all metacognition-based features. However, long-term users of metacognition-based features perform better than the feature’s short-term users. Continued engagement with a metacognitive feature appears to be indicative of higher exam scores. This also implies the possibility of utilizing a metacognitive tool to improve the performance of student outcome modeling by collecting a new type of behavioral data.

1 Introduction

Broadly, *metacognition* means ”thinking about thinking” [1, 2]. Although the specific elements of metacognition vary across the literature [3], some commonly accepted metacognitive activities include planning, self-monitoring, and self-reflecting [4, 5]. For example, a student who engages in a metacognitive activity may plan by allocating time and resources to studying, monitor their learning progress through self-assessments, and reflect on their studying techniques.

Previous research has identified a relationship between practicing metacognition and improved student outcomes in computing, including higher achievement [6, 7, 8], better learning strategies [9, 10], and improved programming skills [11]. However, metacognitive strategies are rarely taught explicitly in higher education [12] and despite foundational research on metacognitive skills, empirical interventions of metacognition are lacking [13]. Most tools primarily focus on offering *cognitive* activities, such as review activities or coding exercises [14, 15, 16, 17]. Furthermore, existing metacognition-based interventions do not capture the entire cycle of studying (planning, self-monitoring, and self-reflecting), or just focus on a specific task of computing education.

Therefore, we developed and piloted CompassX, a web-application that integrates multiple metacognition-based interventions used in prior research. That way, CompassX targeted all three phases of metacognition. The guiding questions of our intervention can be formulated as follows:

- **RQ1:** Do students actually engage with different metacognition-based features throughout a course?

- **RQ2:** How is student engagement with different metacognition-based features related to their learning outcomes?

We deployed CompassX to students in a Data Structures and Algorithms (CS2) course at a public R1 university. We note the goal of the CompassX was to coach students' studying on the conceptual part of the course, not to coach their programming tasks in the course. To ensure that students understood how to use CompassX, we held a mandatory, one-time "workshop" where we demonstrated how to use our tool, explained the metacognition cycle model [18], and briefly presented some research on the empirical benefits to practicing metacognition. Subsequently, we collected data on student usage of the various features of CompassX throughout the term.

Our database records show that students engaged the most with the common quizzing feature. Usage of experimental features including planning prompt, reflection prompt, and evaluation prompt was much lower. Additionally, feature usage spiked significantly during the two midterm weeks. Still, our findings indicate that feature usage on CompassX and learning outcomes are correlated. Long-term users of the quizzing feature outperformed short-term users on midterm 2 and demonstrated higher and more concentrated first-try correctness. For both the planning and reflection features, long-term users performed better than their short-term counterparts. No significant analysis could be performed for the evaluation feature due to the small sample size.

Such correlation between the feature usage on CompassX and learning outcomes imply the potential of CompassX as a measurement tool that reflects students' level of metacognition. Thus, our future work may be 1) how to encourage students to use CompassX more frequently and 2) how to further measure such behavioral data more accurately. CompassX is publicly available at `https://compassx.ucsd.edu/compassx` and we have designed the tool such that new instructors can manage their own classes and set of questions. We encourage instructors interested in using the tool to reach out to the authors of this paper.

2 Related Work

We leveraged the prior work in this section to optimize the learning benefits of CompassX and guide our intervention. Specifically, we developed our metacognitive features to align with Zimmerman's Cyclical Phases Model, which has been investigated in multiple prior research for learning course concepts. The Zimmerman's model is outlined as three phases—forethought, performance, and reflection—of metacognitive regulation [18].

- **Forethought phase:** allocating time and resources to studying (*planning*)
- **Performance phase:** viewing progress reports and reviewing past performance (*self-monitoring*)
- **Reflection phase:** reflecting on one's progress and adjusting one's study plan

(*self-evaluating*).

Section 2.1 describes the benefits of each phase found by prior work. Section 2.2 introduces some existing metacognition-based interventions in computing.

2.1 Benefits of Metacognitive Skills

2.1.1 Forethought

When students fail to plan and structure their study time, they may follow ineffective learning strategies such as procrastination [19] and may earn worse grades [20]. An established link between metacognitive skills and effective time management indicates the need to promote effective metacognitive planning skills [21]. Students who can stick to a habitual study technique have significantly better learning outcomes than students who procrastinate [22, 19]. In fact, Lehmann, Hähnlein, and Ifenthaler found that directed, preflective ("plan out your next study session") prompts that point students towards explicitly planning their studying activities are more effective than generic prompts ("stop and think about your studying") [23].

2.1.2 Performance

Accurate self-monitoring may occur when a student can review their learning progress through visuals such as tables and graphs. Prior work has shown that teaching students how to accurately assess their own abilities leads to an improvement in self-awareness of their skills [24] and that poor self-monitoring may cause students to prematurely stop studying [25, 7]. Work by Bercher tried to improve student's self-monitoring during a lab section by asking students to estimate their mastery of a concept before the lab section and showing students their *actual* mastery afterwards [10]. A majority (87%) of students reported that seeing the discrepancy between their estimated and actual mastery of the material impacted their exam study habits, empirically demonstrating the impact of self-monitoring on study habits.

2.1.3 Reflection

Self-reflecting can involve introspection about one's understanding or evaluating one's progress. It is an important skill not only for conceptual understanding [26] but also for professional development [27]. Prior work indicates that text-based prompts effectively promote reflective thinking among students [23]. Directed reflection prompts, similar to the directed planning prompts, are also an effective way for students to make self-reflections [23]. Empirically, Rasmussen and Stewart found that including a simple prompt that "reminds students to focus on their thinking and asks what they could do differently to learn more effectively" increased the number of students who made a metacognitive reflection in an online forum [28]. Although the *quality* of reflections is prone to subjectivity and difficult to collect, a model developed by Huang, Valdiviejas, and Bosch [29] helps mitigate this issue by counting the number of metacognitive phrases made in a reflection.

2.2 Metacognition-based Interventions in Computing

Metacognition is considered a significant tool for solving problems in computer science. Parham et al. [30] observed that computer science students practice various metacognitive behaviors that cover the entire cycle of Zimmerman's Model. Liao et al. also noted that lower-performing students tend to not fully understand the code they submit for assignments, indicating a lack of metacognitive skills [31].

Moreover, some prior research in computing education has proposed a framework that characterizes metacognitive behaviors of computing students during programming tasks. Loksa et al. proposed the six-staged framework to investigate how self-regulation and metacognition played a role in programming problem solving [32]. However, this framework only focused on programming tasks and the evidence is relatively limited.

Among the three phases of Zimmerman's model, the performance phase is the most commonly investigated. According to Parham et al. [30], this is because self-monitoring is the most widely used metacognitive behavior. Kirkpatrick and Prins [33] and Prather et al.[34] both promoted metacognitive self-monitoring skills to students and found improvement in their learning outcomes. Furthermore, Prather found those who received the treatment were more likely to complete a given programming task.

Less evidence exists about the benefits of the forethought phase, although multiple studies emphasized its importance [35, 36, 37]. This is likely due to the difficulty of isolating the impacts of forethought from other metacognitive skills and activities [38]. Nevertheless, a quantitative study by Zhou et al. [39] found that metacognitive forethought/planning performance was significantly correlated with problem-solving performance in programming activities.

The reflection phase has also not been as broadly explored as the performance phase. Parham's findings also indicated that self-evaluating behaviors are the least used among computing students[30]. Mani and Mazumder do one intervention that encourages self-evaluating behaviors [40]. They asked students to self-report their confidence levels on their answers during a midterm exam. After the graded exams were returned, the students were also asked to reflect on their performance. This study found that such an intervention helps students improve self-awareness of their understanding and learning outcomes [40].

All of the above metacognition-based interventions which only focus on one of Zimmerman's three phases of metacognition, and the majority only target the performance phase. Some other works target specific tasks like programming, but not concept understanding. To our knowledge, no prior work has incorporated the entire metacognitive cycle into a single intervention in computing education. Therefore we built CompassX, a web application to provide a holistic study experience where students can plan, self-monitor, and self-reflect in a comprehensive cycle to optimize their learning strategies [41].

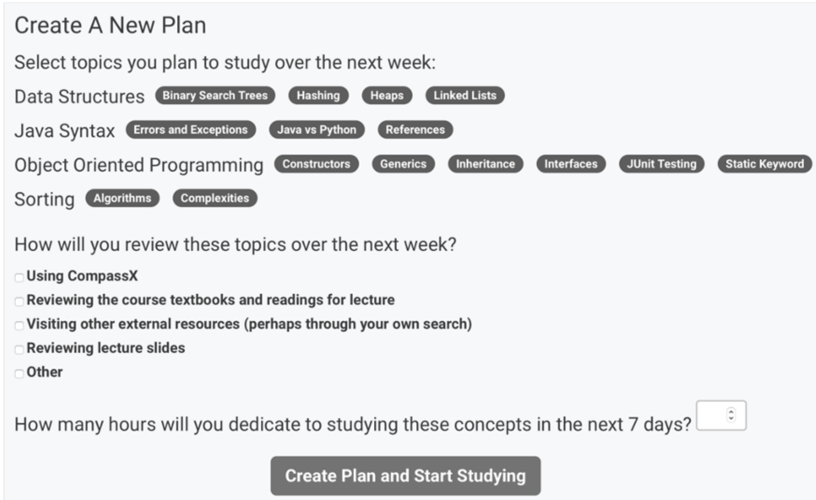


Figure 1: Planning Prompt on CompassX.

3 Key Features of CompassX

We combined a *common* feature from existing quizzing tools with three *experimental* features so that CompassX covers the full range of Zimmerman's Cyclical Phases model.

Customized quizzing is the common feature we integrated and is related to the performance phase. This feature allows users to create a custom quiz by selecting topics and the number of questions in a quiz. The questions are a mix of (1) code tracing questions, in which users are given a piece of code and have to predict the output, and (2) conceptual questions, in which users have to answer scenario-based questions, fill-in-the-blank questions, and various other types to demonstrate understanding of each concept. There are four concepts that the questions cover: Data Structures, Java Syntax, Object Oriented Programming, and Sorting. Each concept consists of three to seven subtopics and there are between 20 to 40 questions available per subtopic in CompassX.

The planning prompt is an experimental feature that covers the forethought phase. It allows users to create their weekly study plan (Figure 1). The idea of the planning prompt is extended from work from Hartwig and Dunlosky,, who found that low-performance users tend to study at night and be driven by impending deadlines [20]. Therefore, our planning prompt aimed to help users better allocate time and resources to studying.

Another experimental feature is the reflection prompt which targets the performance phase. It prompts users to reflect on incorrectly-answered quiz questions (Figure 2) on the results page after they finish a custom quiz. This type of self-monitoring emphasizes reflection on current performance of a single question, as prior work found direct reflections benefits student learning [28].

The evaluation prompt is the last experimental feature and covers the reflection phase. It contains a progress report and an evaluation form (Figure 3), which lets users evaluate their study plan and

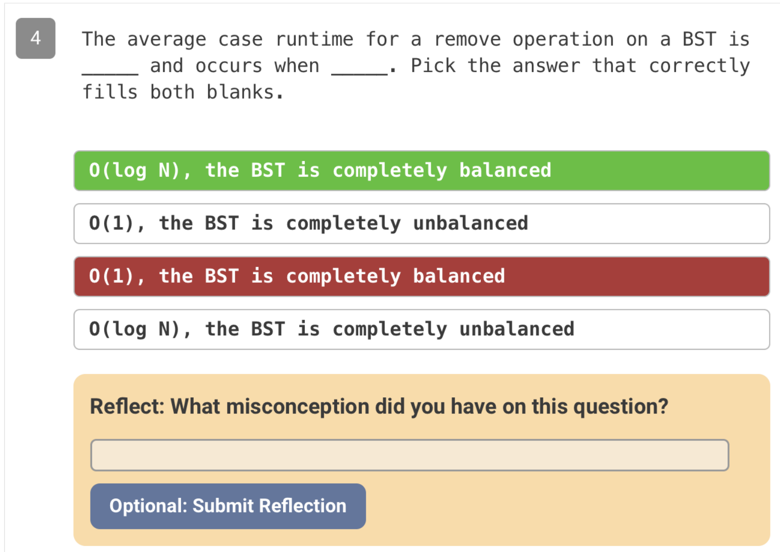
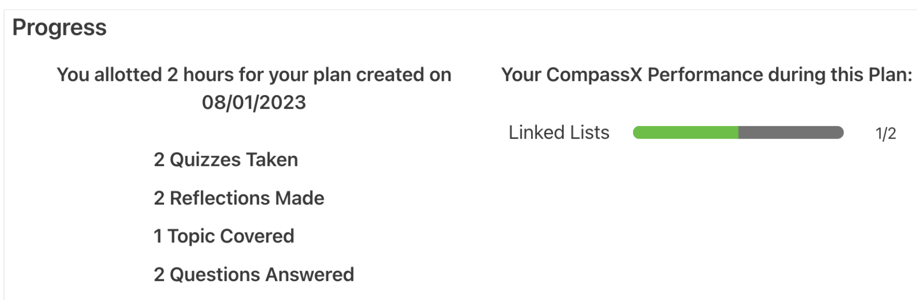
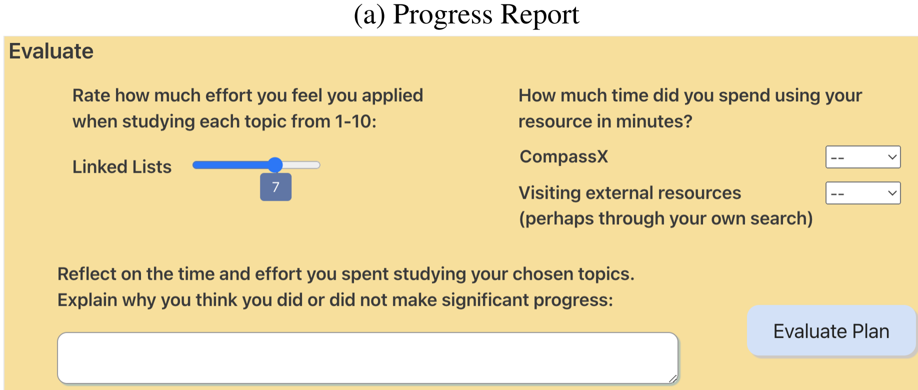


Figure 2: Reflection Prompt on CompassX.



(a) Progress Report



(b) Evaluation Form

Figure 3: Evaluation Prompt on CompassX.

reflect on their performance based on the plan. Users are prompted to compare their study progress with their previously set goal in-depth. Following an evaluation, users can submit a new plan—a feature intended to capture the cyclical nature of metacognition in which self-evaluation promotes adjustments in plans [18, 42].

4 Methods

4.1 User Context

The users of CompassX are students who take the Data Structures and Algorithms (CS2) course at a public, North American R1 university in Winter 2023. The users will be able to learn the syntax of the Java programming language, object-oriented programming, common data structures, and sorting algorithms. The users took the course in 10 weeks, had two midterm exams, and completed a final project.

In week 2 of the term, CompassX was introduced to students through a brief demonstration by a member of the research team. In this "workshop," one of the authors demonstrated the various features of the tool and explained the concept of metacognition to students so that they understood the purpose of CompassX. Attendance at the workshop was worth 2% of students' total grade. For students who were not able to attend the workshop, they were required to answer 15 quizzing questions using customized quizzing and create 3 quizzing questions for CompassX. The users in the workshop were required to submit a reflection on the importance of metacognition.

Throughout the term, CompassX was offered as an optional resource for users. It was accessible to users through the course website from week 2 and users were reminded to use CompassX occasionally during lectures. As a result, we analyze user data that ranges from week 2 to week 10. In total, 101 out of 105 students (96.2%) registered their account on CompassX, and 96 (91.4%) engaged with CompassX at least once within this time frame. We note that some of these users may have stopped using the tool because they dropped the course and others may have enrolled in the course late.

4.2 Data Collection and Analysis

Our findings presented in this paper come from analysis of the CompassX database which records users' plans, answer choices, reflections, and evaluations. Therefore, we can analyze how frequently users completed each of the metacognitive activities.

While investigating the number of unique users each week to capture overall user engagement (RQ1) we found that after the first midterm, most users quit using CompassX. Therefore we focus on comparing the users who used CompassX only until midterm 1 against those who continued to use CompassX even after midterm 1. We note these user groups as the Short-Term users (ST) and the Long-Term users (LT) respectively in this paper. Such grouping allows us to understand who was more willing to use this optional resource, related to their exam performance, and how they engaged with it in more detail (RQ2).

We defined ST and LT for three out of the four key features: customized quizzing, planning prompt, and reflection prompt. They are noted as ST_{Quiz} vs. LT_{Quiz} (30 vs. 60 users), ST_{Plan} vs. LT_{Plan} (35 vs. 3 users), and $ST_{Reflect}$ vs. $LT_{Reflect}$ (26 vs. 6 users). The user data regarding the evaluation prompt feature is dropped for the analysis due to its small sample size (see Section 5.2 for details).

LTs and STs are compared with respect to four different measures: midterm 1 and 2 scores, first-try correctness, the number of unique quiz questions solved for each week, and reflection rate. Midterm 1 and 2 scores are normalized in percentage (%) as each of their maximum possible scores are different. A two-sample t-test was conducted as well to confirm the statistical difference in the midterm scores between ST_{Quiz} and LT_{Quiz}, because their sample sizes were large enough for the test.

To further understand their level of engagement on the customized quizzing feature, we measure the average number of unique questions that ST_{Quiz} and LT_{Quiz} worked on respectively for each week. Users who practice metacognition effectively do not need to repeat the same question as many times as the students who do not. Effective reflection after a quiz fills in gaps in understanding, whereas repeating the same question until a student gets it correct does not.

First-try correctness is the average correctness across all the quiz questions, on the first attempt. For example, if a user has worked on question A three times, only the correctness on their first try of question A will be taken into account. First-try correctness was used upon ST_{Quiz} and LT_{Quiz} to characterize their level of initial understanding of the topic.

Reflection rate is the ratio of incorrect questions whose reflections are also submitted through reflection prompts. For example, if a student got four questions incorrect and submitted reflections on only one of them, the reflection rate of this user is 0.25. We use the reflection rate to measure engagement with the reflection prompt feature.

5 Results

This section presents the effectiveness of metacognition workshops, user engagement with CompassX, and the relationship between CompassX usage and learning outcomes. The results highlight how different levels of metacognitive feature engagement affect student behaviors and their performance.

5.1 Metacognition Workshop

The main purpose of the workshop was to ensure two things:

1. Students know the features on CompassX.

2. Students know about metacognition and its benefits.

Of the 101 registered CompassX users, 78 (77.2%) attended the workshop. At the end of the

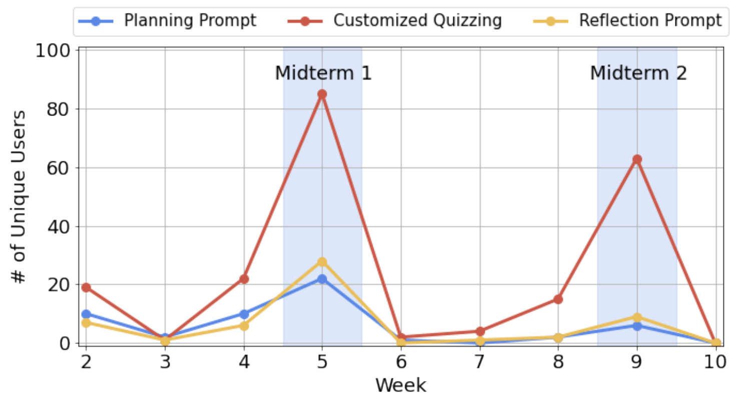


Figure 4: Number of Unique Users per Feature

workshop, the students were required to answer the question "Based on what you learned today, why is metacognition important?" In general, most of the answers from students accurately described that metacognition could help them organize their studying and improve their learning. Of the 90 responses in the workshop, only 8 of them included an overly broad statement such as "effective studying" or a similar vague idea. Many replies indicated the benefits of student learning and studying, and some mentioned specific metacognitive skills such as planning, reflecting, and evaluating.

5.2 User Engagement with Metacognitive Features on CompassX

Figure 4 shows the number of unique users of different key features on CompassX. We observed a spike in the midterm weeks—week 5 and week 9. Our common feature, customized quizzing, was the most used feature on CompassX. Our database showed that 94 (93.1%) of the 101 registered users answered quiz questions at least once during the term. A total of 13,063 questions were answered—an average of about 129 questions responses per user. Among them, 3,168 (24.3%) questions were answered incorrectly.

The experimental features were not as frequently used. Only 61 study plans were submitted throughout the course, and 57 users never made a plan. Moreover, only 28 out of the 85 quiz-takers (32.9%) before Midterm 1 and 9 out of 63 quiz-takers (14.3%) before Midterm 2 submitted reflections on their incorrect answers. Our database records showed that only 186 reflections were submitted out of 3,168 total possible incorrect answers reflections for a rate of 5.9% incorrect answers with a reflection. There were only 9 submitted evaluations throughout the entire term. Among the 9 submissions, three were incomprehensible sentences and another three were duplicates.

5.3 Relationship between the Use of CompassX and Learning Outcomes

Figure 5, 8, and 9 describe the differences between the midterm 1 and midterm 2 scores of LT and ST users of the customized quizzing, planning prompt, and reflection prompt features respectively.

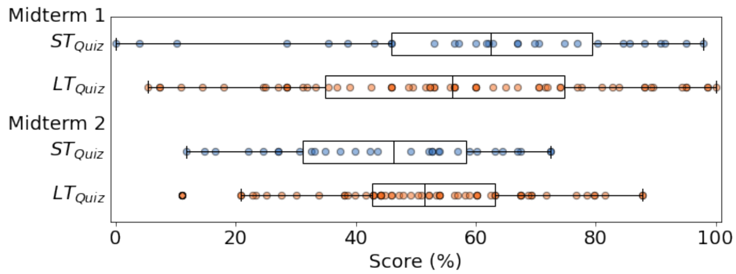


Figure 5: Midterm Scores with Respect to the Use of Customized Quizzing

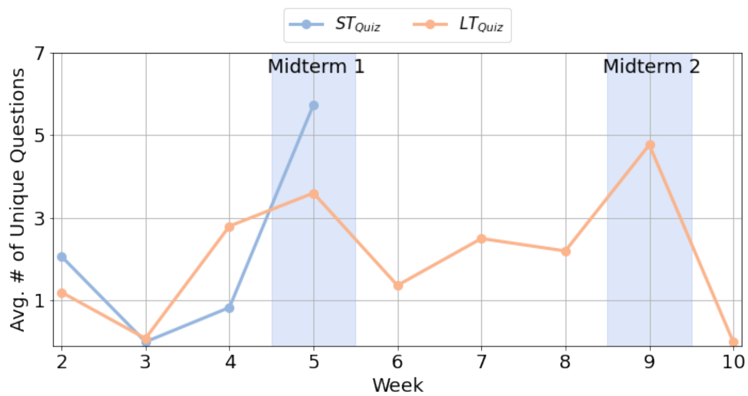


Figure 6: Number of Unique Quiz Questions Solved per Week

Figure 5 shows that while LT_{Quiz} received higher midterm 2 scores than ST_{Quiz} ($p = 0.046$), it was not the case with midterm 1. To be more specific, the median, lower-quartile, and upper-quartile values of LT_{Quiz} seemed lower than those of ST_{Quiz} with midterm 1. However, the t-test results could not confirm the two user groups are statistically significantly different ($p = 0.774$). We found what may have affected this observations from Figure 6. The number of unique quiz questions that are worked on by ST_{Quiz} was comparable on average (8.6 vs. 7.7) within week 2–5 to LT_{Quiz}'s. On the other hand, ST_{Quiz} worked on zero quiz question during week 6–9. In terms of the level of understanding on each topic, the distribution of LT_{Quiz} is more concentrated and most of their first-try correctness are greater than 0.6 (Figure 7).

All LT_{Plan} performed better than the lower-quartile value of ST_{Plan} and two of them were above the median on both midterms (Figure 8). All LT_{Plan} submitted two plans close to the midterm 1 and 2 week respectively, and most ST_{Plan} (77.1%) submitted at least one plan close to the midterm 1 week.

Similarly to LT_{Plan}, $LT_{Reflect}$ received higher scores on both midterms than the lower-quartile value of $ST_{Reflect}$ (Figure 9). Their distribution of the reflection rate on Figure 10 showed that the majority of $ST_{Reflect}$ (65.4%) had a reflection rate less than 0.2 while $LT_{Reflect}$'s reflection rate tends to be more widespread.

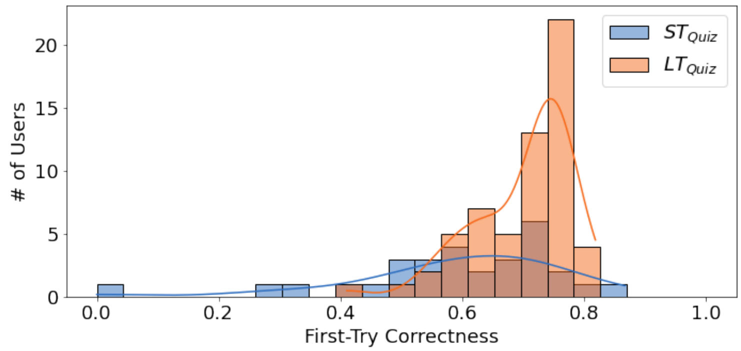


Figure 7: First-Try Correctness with Respect to the Use of Customized Quizzing

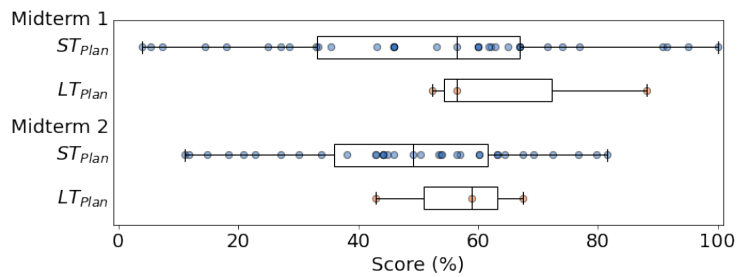


Figure 8: Midterm Scores with Respect to the Use of Planning Prompt

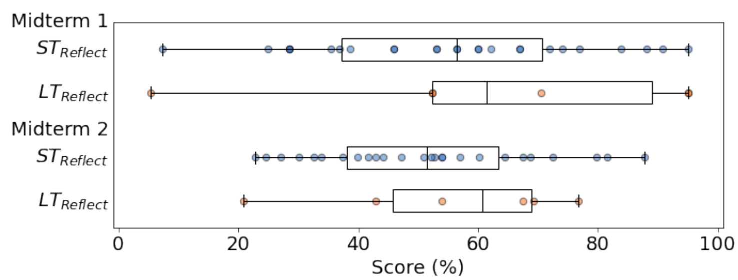


Figure 9: Midterm Scores with Respect to the Use of Reflection Prompt

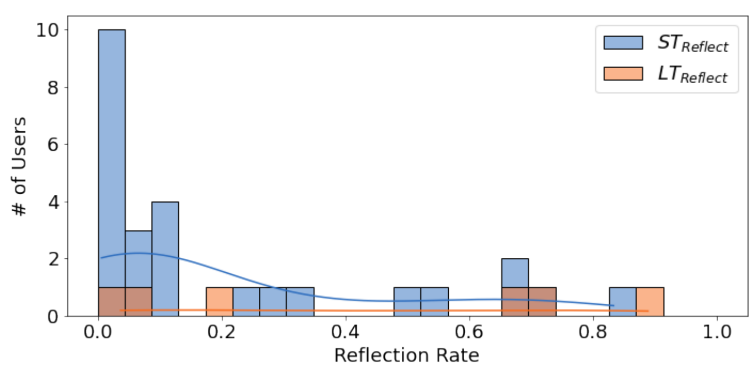


Figure 10: Reflection Rate with Respect to the Use of Reflection Prompt

6 Discussion

This section explores the implications of user engagement with CompassX features and their relationship with learning outcomes, as well as the possible reasons behind. We also discuss potential of CompassX as a behavioral data capturing tool.

6.1 Engagement with Metacognitive Features and Learning Outcomes

The majority of users appeared to perceive CompassX as a self-assessment tool primarily for exam preparation. They utilized CompassX only for a short-term too, as their engagement with CompassX peaked in the few days leading up to the midterms and the usage dramatically decreased as soon as the midterms were over.

Even during this exam preparation period, many users seemed to primarily use the common quizzing features more than the experimental metacognitive features. In the absence of the workshop that we held, we may have suspected that users were unaware of these experimental metacognitive features. However, given that the vast majority of the users attended the workshop, saw the variety of features, and knew of Zimmerman's Cyclical Phases Model, we believe that users' lack of awareness is likely not the cause of the observed results. Rather, we suspect that even after the workshop users still did not see the value in creating weekly plans and evaluating their progress on CompassX.

Despite the overall low engagement, the following observations indicate a positive relationship between the use of metacognitive features and learning outcomes:

- ST_{Quiz} worked on a comparable number of unique quiz questions to LT_{Quiz} until midterm 1; and they performed similarly on midterm 1
- Only LT_{Quiz} utilized the customized quizzing feature for midterm2 preparation; and LT_{Quiz} outperformed ST_{Quiz} on midterm 2
- Only LT_{Plan} submitted plans during midterm 2 preparation; and LT_{Plan} outperformed more significantly on midterm 2
- Only $LT_{Reflect}$ submitted reflections during midterm 2; and $LT_{Reflect}$ outperformed more significantly on midterm 2

As the positive effects of metacognitive tool use are obscured by low use, future work may identify how to encourage users to engage with the metacognitive features more frequently.

6.2 CompassX as a Measurement Tool

Although we did not see a sustained, high engagement with all four metacognitive features, we still believe that our tool lays sufficient groundwork for future interventions. CompassX can serve as a measurement tool of students' use of metacognitive activities for various classroom interventions seeking to improve student engagement with such activities. Given the relative ease of data collection via a built-in database and Google Analytics tracking, we plan to use CompassX to monitor students' engagement with various phases of the metacognition cycle. The capability of collecting a new type of behavioral data - the engagement level with metacognition activities - could potentially be used as well in the field of educational datamining. Given that most existing datamining work utilizes learning-outcome-based data (e.g. quiz scores, code compilation histories), our data which is more deeply grounded in educational psychology could help improve modeling performance.

7 Threats to Validity

Our analysis in this paper is based on a single cohort from a single course so our findings may not be consistent with a different cohort or with a different course. However, we believe our results still provide some insights into how students actually engage with metacognition-based interventions and how we can collect students' metacognitive behaviors in a systematic and scalable manner. We also present the overall distribution of the results to minimize the effect from the small dataset.

8 Conclusion

We performed an intervention integrating a metacognitive learning tool called CompassX to support all phases—forethought, performance, and reflection—of metacognitive regulation. Specifically, students could plan their studying (planning prompt), self-monitor their progress and comprehension (customized quizzing), reflect on specific misconceptions they had (reflection prompt), and self-evaluate their weekly progress (evaluation prompt). Our data showed that the users primarily engaged with the customized quizzing feature during exam weeks only rather than the experimental features we added relating to planning, self-monitoring, and self-evaluating. However, those who utilized the metacognitive features more and in the long-term performed better than those who did not.

CompassX is ready to be shared with instructors who would also like to 1) collect data on and/or 2) promote metacognitive regulation among their students. We urge interested instructors to reach out to the authors of this paper to implement CompassX in their own class.

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