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Optional Self-Explanation Tasks in Practice: Participation Rate, Explanation Quality, and Performance

Steven Moore, George Mason University, StevenJamesMoore@gmail.com
Sreecharan Sankaranarayanan, Amazon.com, Inc., sreecharan93@gmail.com
Huy Nguyen, Amazon.com, Inc., anhhuy0706@gmail.com

Abstract: The benefits of self-explanation for learning have been well researched, yet we know little about whether students engage in self-explanation when the tasks are optional. This study investigates participation rates, explanation quality, and their correlation with student performance in an introductory online chemistry course with 129 students. We found that 53% of students voluntarily participated in an optional self-explanation activity and 66.18% of their self-explanations were judged as high-quality by experts. Self-explanation quality was positively correlated with student performance in the course, as measured by formative and summative assessments. These results suggest that while optional self-explanation tasks effectively attract students overall, the intervention may primarily be supporting already high-performing students. Nevertheless, the high quality of generated self-explanations indicates that keeping the activities optional while focusing on increasing the rate of participation could lead to better outcomes at scale when compared requiring mandatory participation.

Introduction

Self-explanation is a constructive learning activity that fosters deep learning by encouraging students to generate inferences to themselves while they engage with the learning material. The "self-explanation effect" is well documented in learning science literature discovering, for instance, that *"students who explain examples to themselves learn better, make more accurate self-assessments of their understanding and use analogies more economically while solving problems"* (VanLehn et al., 1992). In particular, self-explanation acts as a medium for developing students' thinking and is specifically important for fostering transfer between concepts (Margulieux & Catrambone, 2017; Wylie & Chi, 2014). In a variety of domains, prompting students to self-explain while learning has been shown to positively impact the development of both conceptual and procedural knowledge (McLaren et al., 2022; Rittle-Johnson, 2006). Understanding the structure and the quality of students' self-explanations can provide a foundation for examining their learning progression and their ability to communicate science (Sandoval & Millwood, 2005). By examining the coherence and depth of students' explanations, researchers and educators can diagnose misconceptions, track conceptual development, and assess students' emerging ability to articulate scientific reasoning.

Self-explanation can be elicited through various interventions, such as explaining out-loud to a person (Jacob et al., 2020), selecting an explanation from a list of options (Asano, Dutta, et al., 2021), responding to a conversational agent prompt (Sankaranarayanan et al., 2020, 2022), or constructing one's own while scaffolded by open-ended, elicitation prompts or contributions from peers (Asano, Sankaranarayanan, et al., 2021; Rittle-Johnson & Loehr, 2017). This set of previous work has shown that it is effective for both in-person instruction in the classroom and online, at scale, in a digital environment. In either context, self-explanation activities are typically mandatory for students as a part of their coursework or participation in a study. From a controlled research standpoint, this allows claims to be made about the relation between the quality of the student's explanation and their success in class (Menekse et al., 2011). Additionally, systems are sometimes developed and deployed specifically to engage students in the self-explanation process (Williams et al., 2016). Without such forcing functions that require the students to complete the task, the participation rate in and success of self-explanation activities remain unclear.

From a practical standpoint, optional self-explanation activities can be incredibly lightweight and easy to deploy at scale, such as with optional open-ended prompts to self-explain, as described in Asano et al. (2020). This means that the benefits of self-explanation on learning could be realized without the need of additional grading or ed-tech tooling. However, we need to first understand how students will interact when the self-explanation activity is optional and for those that do interact, what the quality of their self-explanation is like. We addressed these questions in this paper by including an optional self-explanation prompt in an online chemistry course taken by over a hundred students. This study contributes new knowledge about student participation with optional tasks in an online course, particularly one involving self-explanation. It also provides evidence for how student performance correlates with the quality of their self-explanation. Finally, observing that students who choose to participate in the self-explanation activities produce high-quality self-explanations produces design

implications for future self-explanation tasks at-scale. In particular, the implication is that more success may be had from intervening to improve the rate of participation in optional self-explanation activities, rather than simply requiring them of all students.

Theoretical Framework

Self-explanation has been proven to be an important cognitive process beneficial to meaningful learning that can support transfer and help develop metacognitive skills (Vieira et al., 2019). By having students articulate and reason through a concept or why they chose a particular answer, self-explanation activates deep-level cognitive processes, such as organization and integration of information (Pilegard & Fiorella, 2016; Chen et al., 2025). Fiorella (2023) situates self-explanation within a broader framework of generative learning strategies, emphasizing that such activities are most effective when learners meaningfully select, organize, and integrate new information with prior knowledge rather than passively reviewing material. Many studies have demonstrated that self-explanation is not only effective when done verbally or as a physical activity in the classroom, but it is also an effective intervention for online instruction (Menekse et al., 2011; Sankaranarayanan et al., 2020, 2022; Williams et al., 2016). For example, a study by Menekse (2020) had students submit self-explanations using a mobile learning platform after each class lecture they attended. They found that students who submitted the explanations performed significantly better than students in the control condition on the four summative assessments given throughout the course.

When investigating self-explanation, many studies require participants to complete the self-explanation prompt as part of their graded coursework or for financial compensation as part of a study (Fan et al., 2015; Lisk et al., 2017). This is not necessarily reflective of what usually occurs within an in-person or online course, as self-explanation can be completely optional and not graded or reviewed by the instructor. Asano et al. (2020) conducted a study that embedded two optional self-explanation prompts into online homework problems for an introductory course on programming. They found that students who scored poorly on the homework questions and spent less time solving the questions were less likely to participate in the self-explanation activity. This is one of the few, if only, studies that presents students with the option to do the self-explanation in an online coursework context, instead of requiring them to do it for grade or study purposes.

Evaluating the output of students' explanations has been another area of prior research, utilizing either natural language processing methods to automatically assess them or having experts with a rubric judge the quality of the explanations (Luo & Litman, 2015; Vieira et al., 2019). Recently, many studies have leveraged a four or five point rubric to evaluate student self-explanations in a variety of domains (Asano et al., 2020; Luo & Litman, 2016; Menekse, 2020). In these studies, expert reviewers familiar with the course content review student-contributed self-explanations and determine their quality based on a set of criteria, such as if the explanation is vague or copies text from the question. Additional studies, such as Menekse et al. (2011), had students self-explain and reflect on confusing concepts during their coursework in an engineering course. The results demonstrated that the quality of student self-explanations positively correlated with student learning gains, as measured by pre- and post-concept tests and unit exams.

In this study, we present students with an optional self-explanation prompt embedded in their online coursework. We then utilize a 5-item rubric to assess the quality of students' self-explanations and analyze how they relate to performance in the course. The specific research questions we address are:

RQ1: To what extent do students voluntarily participate in an optional self-explanation activity in an online chemistry course?

RQ2: What is the quality of students' self-explanations when participation is optional?

RQ3: How does the quality of students' explanations relate to their performance in the course?

In answering these research questions, we aim to derive recommendations for the design and inclusion of self-explanation tasks in online learning environments.

Methods

Learning platform

This study uses the Open Learning Initiative (OLI), a digital courseware platform that delivers courses across multiple disciplines through interactive activities and multimedia instructional content (Bier et al., 2019). Activities within OLI fall into two categories of formative activities that are low-stakes and provide immediate feedback and summative assessments that evaluate student learning at the conclusion of each unit. All formative activities are optional, so students may bypass them entirely and engage only with the instructional text. These activities are made up of several formats, including multiple-choice questions (MCQs), short answer prompts, and drop-down selections. OLI structures each question as a series of one or more discrete steps, with each step

representing a single opportunity for student input and having its own feedback. For example, a question requiring three drop-down selections would comprise three independent steps. This granularity matters because students frequently engage with some steps of a problem while leaving others incomplete, whether due to uncertainty, time constraints, or disengagement (Chen et al., 2018).

Student context

We used data collected from a week-long unit in four instances of an introductory chemistry course taught at a community college in the western United States. The course is geared towards freshman and sophomore undergraduates from varying degree backgrounds, with a majority of the students pursuing a chemistry-related degree. We chose data from the fall semester of 2020, prior to the LLM-era of education, when the introductory chemistry course was offered in the OLI system. It provides a clean baseline for understanding authentic self-explanation behavior before generative AI could confound participation and quality measures, establishing a necessary foundation against which future LLM-era studies can be compared. We discuss the implications and possible modifications to self-explanation activities in response to LLM use in our Limitations and Future Work section (Van Wyk, 2024). For this study, we can mitigate concerns about widespread use of generative AI for such activities today and observe the effects more clearly. In total, our data consists of 129 students, with 68 of them participating in the self-explanation activity. Additionally, the course was fully remote delivered online for students due to the COVID-19 pandemic.

The OLI content the students used for the course covers the topic of elements and compounds and consists of thirteen separate modules. Each module consists of several topic headers, containing paragraphs of instructional text and low-stake activities embedded throughout. There are a total of 35 low-stakes and completely optional problems embedded throughout the thirteen modules of the course. These problems include multiple choice questions, selecting the correct option from a drop-down, drag-and-drop exercises, and submitting a short answer to compare against an expert response. Each of these problems is broken down into steps, depending on the components of the activity, for a total of 178 unique steps. For instance, if a problem has three fill-in-the-blank boxes, then that problem would consist of three unique steps. Additionally, students have unlimited attempts to answer these questions, so they can continue until they are correct or choose to advance, regardless of a correct or incorrect response.

While the four course instances were taught by different instructors, students were provided with the same set of instructions regarding the use of the OLI materials. They were not required to answer the questions found throughout the OLI modules. Students across all instances were granted access to the OLI content the first week of their respective course. They were also provided with an “Introduction to OLI" module, which is an overview of how to effectively make use of the system and the concepts that will be covered in the course. All the instructional materials in OLI were optional to the students; there was no requirement for them to access or complete the materials outside of the summative quiz that was also accessed and implemented in the OLI platform. However, students were assessed on the concepts covered by the OLI materials elsewhere in the course, so it was beneficial for the students to utilize them. A further breakdown of the course offerings, including the instructor, semester, and number of students that accessed the course materials can be found in Table 1.

Table 1

The four introductory chemistry courses used in this study

Course	Semester	Instructor	Student Count
course1	Fall 2020	t1	57
course2	Fall 2020	t1	26
course3	Fall 2020	t2	23
course4	Fall 2020	t3	23

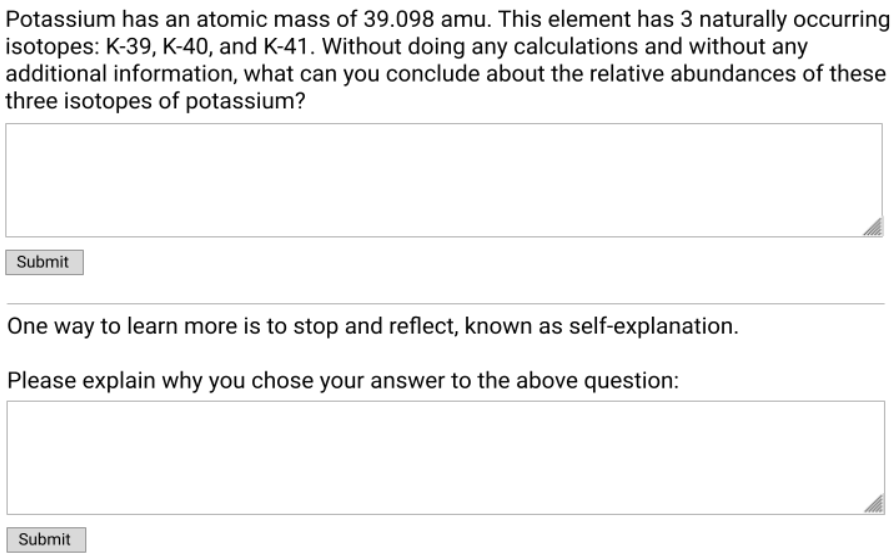
Data collection

Our analysis focuses on a self-explanation activity embedded within the course where students are asked to articulate why they selected their answer to a preceding problem. This activity appears in the second module of the course unit, which covers the topic of atomic mass through instructional text, two worked examples, and several optional multiple-choice and short-answer questions. Consistent with the other formative activities in the course, the self-explanation activity is ungraded and entirely optional. As shown in Figure 1, students encounter a short-answer question followed by an open-ended prompt asking them to explain the reasoning behind their response. The prompt language, adapted from Asano et al. (2020), was designed to briefly introduce self-explanation as a learning strategy while maintaining student motivation to participate. By preserving the optional

and low-stakes nature of this activity, we were able to observe authentic patterns of student participation and assess the quality of their contributions without the confound of grade-based incentives.

Figure 1

The self-explanation activity and accompanying question presented to the students



Analysis

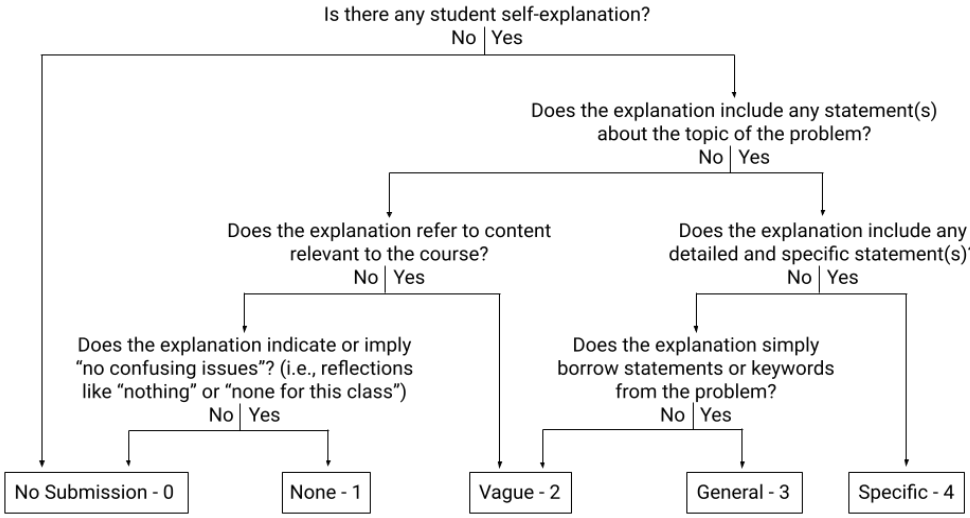
The student-generated explanations were coded by two experts to assess their quality and specificity. In the present study, we opted for expert rubric coding rather than evaluation using natural language processing due to our sample of 68 explanations which made manual coding feasible and prior research demonstrating that human application of rubrics is still the gold-standard approach (Moore et al., 2024). The two experts had content knowledge in chemistry and had ample previous experience coding qualitative student data. The interrater reliability was calculated and the Cronbach's alpha value was .98, as the raters only disagreed on the rating of four self-explanations. These discordant explanations were discussed among the two raters until they reached a consensus on the categorization of them using the coding schema. This coding schema was adapted and used from Menekse (2020), which has also previously been used in several studies (Asano et al., 2020; Lisk et al., 2017; Luo & Litman, 2016; Menekse et al., 2011). Explanations were assigned scores from the rubric ranging from 0 to 4. Figure 2 illustrates the exact coding schema that was utilized by the two expert reviewers. A score of 0 "No Submission" means that the student left the self-explanation text box blank, they did not submit anything. Explanations received a score of 1 "None" if the student submitted something, but it was not relevant to the problem or the course content in any fashion. For example, a student wrote "I had no idea what to say, but I had to say something". While the student did input a self-explanation, it has no relevance to the context of this course and it appears as if they were just submitting text to have something input for this question. A score of 2 "Vague" was assigned to explanations that were not specific to the current problem, but were still relevant to the context of the course and potentially borrowed some language from the question's text. One example submitted by a student was "they have to be within range of the isotopes". While part of the problem does involve isotopes and they are mentioned in the text, this explanation only mentions the isotopes and does not reference how the isotopes impact the outcome of the problem. Additionally, it is not clear what the "they" is referencing in this explanation.

Explanations received a score of 3 "General" if they discussed the topic of the problem, but did not provide enough details. For example, one student wrote "It is the number closest to 39.098 amu." for their explanation. This explanation directly relates to the problem and even a number used in calculating the correct answer, but does not mention specifics on how to use the amu number or the isotopes to determine the correct answer. Finally, a score of 4 "Specific" was given to explanations that were both detailed in nature and specific to the problem, for instance "The atomic mass is the average mass of all the isotopes present in a naturally occurring sample of this element. If the amu for K is 39.098, then that means that K-39 is more abundant since it is the closest to the atomic mass". Note that this explanation is also much longer than the previous, which was a trend for the explanations scored in this category. The explanation, in sufficient detail, clearly demonstrates how the students used their knowledge of atomic mass and isotopes to determine the correct answer. We note the

present study uses optional activities and because participation was voluntary, our analyses are observational rather than experimental. As a result the associations reported between self-explanation quality and performance should be interpreted as correlational patterns rather than causal effects.

Figure 2

The adapted flowchart rubric used to review student self-explanations.



Results

To understand how students participated with an optional self-explanation activity, we first analyzed their participation throughout the course. For the students that participated, we then assessed the quality and descriptors of their self-explanations to determine how they interacted with the optional task. Finally, we present the correlations between formative and summative student performance in the course and their contribution to the self-explanation task. A Bonferroni correction was applied to post hoc analyses that follow (Armstrong, 2014).

Student participation and engagement

Across the four course instances, 68 of 129 students (52.71%) voluntarily submitted a response to the self-explanation activity. To contextualize this participation rate, the course unit contained 35 formative problems comprising 178 individual steps, all of which were optional. Students engaged with a substantial portion of these materials, completing an average of 22.66 problems (SD = 14.67) and 112.96 steps (SD = 78.54). We found that students who participated in the self-explanation activity completed significantly more problems, $t(127) = 9.369$, $p < .0001$, and steps, $t(127) = 9.319$, $p < .0001$, than those who did not. This suggests that self-explanation participants were broadly more engaged with the optional course materials.

The self-explanation prompt followed a short-answer question positioned early in the course, which 83 students (64.34%) attempted. Of these students, 15 of them answered the preceding question but chose not to continue and complete the self-explanation task. This indicates a deliberate opt-out, rather than a failure to encounter the activity. Students spent an average of 99.82 minutes (SD = 82.99) actively working on course problems overall, as measured by typing or cursor activity within activity fields. Time investment in the self-explanation task itself averaged 103.58 seconds per student, ranging from 17 to 433 seconds.

Student explanation quality

Students entered their self-explanations into a resizable multi-line text field with no constraint on the required length. Their responses averaged 21 words, ranging from a single word to 68 words. The time students spent on the activity was positively correlated with their explanation length, $r(67) = .28$, $p = .019$. This suggests that students who invested more time were actively composing their responses, rather than passively dwelling on the task. A Spearman's rank-order correlation also revealed a positive association between time spent and the rubric score assigned to the explanation, $rs(67) = .26$, $p = .032$, indicating that greater time investment corresponded with higher-quality contributions.

Table 2 presents the distribution of rubric scores across all students. Across these 129 students, 61 (47.29%) did not submit a self-explanation. Among the 68 who did, two-thirds (66.18%) received scores of 3 or 4, meaning their explanations were relevant to the problem. This involves either addressing the topic at a general

level (score 3) or demonstrating detailed and problem-specific reasoning (score 4). The proportion of high-quality explanations was also relatively stable across course instances. The highest rate of score-4 explanations appeared in course2 (19.23% of all students in that instance), but a one-way ANOVA confirmed no significant differences in the distribution of rubric scores across the four courses, $F(3, 125) = 1.309$, $p = .274$.

Table 2

Distribution of expert-assigned rubric scores for student self-explanations across the four course instances.

Course	0	1	2	3	4	# of Students
course1	30	3	2	15	7	57
course2	9	1	3	8	5	26
course3	12	3	3	2	3	23
course4	10	4	4	3	2	23
Total (%)	61 (47.3)	11 (8.5)	12 (9.3)	28 (21.7)	17 (13.2)	129
Total (%) of Non-Zero Scores	-	11 (16.2)	12 (17.5)	28 (41.2)	17 (25)	68

Student performance correlations

We utilized the optional problems and their steps found throughout the modules in the course as our formative measures of student performance. We hypothesized that students who perform better on the course's assessments would also contribute higher quality self-explanations. To investigate how the quality of students' self-explanations correlates with their performance on the formative and summative assessments found in the course, we divided the students into four groups, based on the score (1-4) of their self-explanation responses (those who did not submit self-explanation prompts are excluded from this analysis). We then conducted an ANOVA to compare the number of steps they answered correctly on the first attempt, which serves as an accuracy metric for assumed student knowledge about the skills a problem assessed (Bier et al., 2019; Heffernan & Heffernan, 2014). Our results revealed a significant difference in the number of correct-on-first-attempt steps between the score groups, $F(3, 64) = 3.064$, $p = .034$. A post hoc (Dunn) showed that the following pairs of student groups had significant difference in the number of correct-on-first-attempt steps: 1-score and 4-score ($p = .008$), 1-score and 3- score ($p = .031$), 2-score and 4-score ($p = .019$). Note in particular the lack of significant difference between 3-score and 4-score indicating that both may be of sufficiently high-quality. However, there was no significant difference in time spent on problem solving in the course between the four score groups, $F(3,64) = 0.824$, $p = .486$.

Upon completing this unit, students were required to take a quiz about the topics of the modules as many times as they liked until they achieved a score they found satisfactory. Including the students that did not submit a self-explanation, using a one-way ANOVA, we did not find a significant difference for the number of quiz attempts students made between the rubric scores they received, $F(4, 124) = .426$, $p = .789$. However, another ANOVA revealed a significant difference between the rubric scores for the first attempt quiz score, $F(4, 124) = 5.108$, $p < .001$, suggesting that students who received a higher self-explanation score performed better on their first attempt at the quiz. A post hoc (Dunn) showed that the following pairs of student groups had significant differences in the first attempt quiz score: 0-score and 3-score ($p < .001$), 0- score and 4-score ($p < .001$), 1-score and 3-score ($p = .042$), 1-score and 4-score ($p = .006$). As before, of particular note is the lack of significant difference between 3-score and 4-score. Relatedly, there was also a significant difference between the different rubric scores and the final quiz score students found satisfactory, $F(4, 124) = 3.112$, $p = .018$. Post hoc (Dunn) showed that the following pairs of student groups had significant difference in their final quiz scores: 0-score and 3-score ($p < .001$), 0-score and 4-score ($p = .018$), 1-score and 3-score ($p = .007$), 1-score and 4-score ($p = .043$).

Regardless of the rubric score they received, an unpaired two-tailed t-test showed that students who participated in the self-explanation task had a significantly higher first quiz attempt score than those who did not do the self-explanation activity, $t(127) = 3.807$, $p < .001$. Similarly, a significant difference was found between participation in the self-explanation task and the final quiz score students found satisfactory, $t(127) = 3.475$, $p < .001$. To investigate this further, we omitted students that did not submit a self-explanation and conducted a Mann-Whitney U-test between rubric groups for students that got a B average of 80% or higher on the first attempt of the quiz. We found that there was a significant positive correlation between this quiz first attempt and the rubric score students received, $U = 1091.5$, $Z = 3.714$, $p < .001$. These results indicate that both participation in the optional self-explanation activity and the quality of students' explanations are systematically and positively associated with performance on formative and summative assessments. However, we note the direction of this relationship, whether self-explanation supports performance or higher-performing students self-select into the activity, cannot be determined from these data alone.

Discussion

In this study, we investigated participation, explanation quality, and performance associations for an optional self-explanation activity in an online chemistry course. Over half of students (52.71%) voluntarily participated, with 66.18% of submissions rated as high-quality. Both participation and explanation quality were positively associated with formative and summative assessment performance, though the pattern of results suggests that already high-performing students may be the ones choosing to engage.

First, we found that even when a self-explanation activity is optional, knowing it will not be graded or give the students credit, they will still engage with it. Since the OLI materials, outside of the summative quiz, were supplemental and completely optional, we hypothesized that many of the problems, especially the short-answer questions, would be skipped by a majority of the students. However, students in the course trended towards two different approaches of using the materials. One set of learners would at least answer all of the optional formative questions once, potentially to just mark them as completed or receive any feedback they might offer, a prevalent strategy for online coursework (Chen et al., 2018). The other set of students skipped most of the formative questions in the modules and only completed the summative quiz at the end of the unit. On average, the self-explanation activity took students around 103 seconds to complete, which is enough for students to critically reflect on their thinking and is a common time allotment for related activities like the muddiest point (King, 2011).

Second, we found that a majority of the self-explanations contributed by students were rated as "General - 3" or "Specific - 4" based on our rubric in Figure 2, suggesting that they meaningfully engaged with the activity, despite it being optional. As expected, the more time a student spent on the self-explanation activity, the more likely it was for it to be both longer and scored higher by the reviewers. For all the non-zero scores, where students made a submission to the self-explanation task, the most common score was a 3. This indicates that their self-explanation was about the topic of the problem, but still lacking some specificity that might provide further insight into their thought process. Elevating students, perhaps by prompting them to provide more details or to keep in mind that they should be specific when possible, might improve the quality of their contributions further. Currently, as seen in Figure 1, the prompt briefly mentions "self-explanation" as a strategy for learning and asks students to explain their answer. A more detailed prompt could say - "the more detailed your explanation, the more it is reflective of your understanding of the idea – so we encourage you to write a detailed explanation about why you chose your answer". This could help with increasing the uptake of the intervention as well. Additionally, it was promising to find so few self-explanations being scored as 1 or 2, suggesting that students who participated in the self-explanation activity were making a valid attempt at the process. It is possible to hypothesize that it is the optional nature of the activity that leads to the higher quality of submissions. In other words, the fact that the activity was optional meant that the students who would have not contributed meaningfully choose not to engage and those who did engage, made predominantly meaningful contributions. As prior research (McNamara et al., 2006) has established, while participating in self-explanation already produces positive effects, the higher the quality of the self-explanation, the higher the performance. Interestingly, 15 students did the short-answer question that preceded the self-explanation task but chose not to submit an explanation. Further research remains to be done on how we might engage those students that are close to the activity or to find out why they chose to not submit anything despite presumably seeing it. Possible interventions could include added context about the value of self-explanation, especially high-quality self-explanations, to their learning, using an improved prompting strategy as suggested above, or, by having the course instructors encourage students to complete such activities (Menekse, 2020).

Third, both participation in the self-explanation task and the quality of the explanation were positively associated with students' performance on the assessment items in the course, in line with previous research (Moore et al., 2021). Our analysis revealed that the quality of students' self-explanations was positively correlated with their performance on the formative assessments. However, no significant correlation was found between the time a student spent working on activities and their self-explanation score. While not suggesting that self-explanation improved the performance of students to that level, it does suggest that the higher-performing students were the ones doing the activity, which corroborates the results of a related study (Asano et al., 2020). Similarly, the assessed quality of a student's self-explanation was also positively associated with a higher score on the first attempt and final score on the summative quiz at the end of the unit. We did not find an association between the self-explanation rubric score and the number of quiz attempts made by students. Students typically made two or three quiz attempts before accepting the final score they received on it. While having high-performing students complete the self-explanation is still beneficial, in the future we would like to investigate how to target those who are not performing as well in the course.

In studies where all students, regardless of whether they are already set to be high-performers, have to do self-explanations, beneficial effects have been realized for all of them, as discussed in the Theoretical Framework section. However, the quality of these explanations, at least for a subset of learners, tends to be

questionable owing to the mandate (Asano et al., 2020). In the case where it remains optional, we see a consistently high quality of self-explanation with the caveat that currently, predominantly high-performers are participating in them. Therefore, the question of whether appropriate interventions, that encourage currently non-participating students to contribute these self-explanations, can result in higher-quality ones and increase performance remains open. In other words, will requiring all students to engage in self-explanations be better for them, or will providing a choice to them while pairing that choice with the appropriate intervention result in better quality self-explanations and resulting out-performance? The results of this study imply that the latter could be more impactful, suggesting a nuanced path forward for integrating self-explanation activities into online learning environments. Additional opportunities for self-explanation could also be recommended to students prior to starting their summative assessments, so that they remain optional, but are more likely to get viewed by students on a task that they are required to complete. These students could potentially benefit from the self-explanation intervention more, as previous work has highlighted the benefits of self-explanations, particularly for novice learners (Lisk et al., 2017). Finally, future work has to contend with designing self-explanation activities in the era of LLM use.

Limitations and Future Work

While we have uncovered relatively clear relationships between students' course performance and self-explanation quality, there are limitations that influence the interpretation of our results. First, our study relies on student data from optional activities found throughout the course. Our findings are prone to a self selection bias, as participants in the self-explanation task might be the most driven students that want to complete all of the materials. Second, students' background both in the knowledge domain and their familiarity with similar meta-cognitive tasks may also impact their self-explanation output. Additionally, we conducted the study on one problem, although spread about four separate course instances of chemistry, for which the course content might impact the task and student performance. Thus, more research is needed to validate the generalizability of our findings, across different domains and contexts at scale.

One clear direction for future work is investigating if interventions can increase the rate of participation in self-explanation activities and if performance continues to be positively impacted by that participation. Experimentally contrasting this against requiring self-explanation for all students to compare their respective impacts on student performance, is another future direction that will produce implications for contexts at scale. A differentiator today is the availability and prevalence of LLMs, which present both challenges and opportunities. The challenges are obvious, as students might resort to LLM assistance to complete self-explanation activities, undercutting the learning benefits. Once again, optional self-explanation activities could prove beneficial as the incentive to resort to assistance may not be as strong owing to the optional, ungraded nature of the activities. Viewed positively, these may even be sites for teaching students not to "cheat themselves" out of learning opportunities (Uhlig et al., 2024). In particular, LLM-generated scaffolds for self-explanation could provide more encouragement and support for students for whom this was the blocker to engagement (Wen, 2025).

Conclusion

Ultimately our study makes two practical contributions. First, we provide insights into the engagement of real-world students in an online course with optional activities and a self-explanation prompt. Second, our results suggest that higher performing students were more likely to participate and have a higher quality contribution to a self-explanation task. Many studies have demonstrated the effectiveness of self-explanation, however very little work has been done around providing students with the option to do the self-explanation in a naturalistic setting, where they do not receive incentives for their participation. This study has shown how students authentically contributed to the self-explanation task and suggests that the students participating in such interventions might already be the most driven and knowledgeable ones. It also produces design implications for improving the quality of self-explanations and ways to encourage non-participants to contribute explanations that are decidedly of higher quality than if they were simply forced to do so.

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