Participation and Success with Optional Self-Explanation for Students in Online Undergraduate Chemistry Courses

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Abstract: The benefit of self-explanation in learning has been well researched, but the extent to which students engage with such activities in a real-world course setting is often overlooked. To investigate how students participate and perform on such a task, we embedded an optional self-explanation activity into an introductory online chemistry course consisting of 129 students. We analyzed their participation and performance in the course, and how it relates to the quality of their self-explanation. We found that 53% of students participated in the optional self-explanation activity and 25% of their self-explanations were reviewed by experts to be sufficiently specific and detailed. Our results suggest that students are willing to engage with an optional self-explanation activity; however such interventions may be targeting the already high performing students in the course.

Introduction

As a constructive learning activity that fosters deep learning by encouraging students to generate inferences to themselves while they engage with the learning material, 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 (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). Self-explanation can occur through different modalities, such as explaining out loud to a person (e.g. Jacob et al., 2020), selecting an explanation from a list of options (e.g. Asano et al., 2021), and constructing your own via an open-ended prompt (i.e., self-explanation - 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 in a digital environment. Oftentimes students are required to perform self-explanation as part of their coursework or participation in a study, so claims can be made in relation to the quality of the student 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). As a result, the participation and success of self-explanation activities may be inflated, as students in online courses often lack motivation and have low participation rates when the material is not required (Shapiro et al., 2017). This is not necessarily reflective of what occurs in the classroom or online, where students often make use of more low-stakes learning opportunities intended to give students feedback that are not required for the students to complete.

As prompting students for self-explanation has been proven to be an effective instructional intervention, garnering the participation of students that are struggling and could benefit the most from it is critical. While often neglected by previous work around self-explanation, identifying which students are engaging in the task, particularly when it is optional, can improve understanding of how self-explanation is leveraged by students. As stated in Asano et al. (2020), optional open-ended prompts to self-explain can readily be applied into many courses without the need of additional grading or ed-tech systems. 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 the current work through including an optional self-explanation prompt in an online chemistry course taken by over a hundred students. Specifically, 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. The two research questions we address are: (1) How often do students engage with an optional self-explanation activity in the context of their online chemistry course? and (2) How do students respond to optional self-explanation prompts in an online chemistry course?

Methods

Study context & students

The present study takes place in a digital courseware platform known as the Open Learning Initiative (OLI). OLI is an open-ended learning environment that offers courses from a variety of domains (such as chemistry, biology, statistics, economics, etc.) and consists of interactive activities and diverse multimedia content (Bier et al., 2019). OLI activities are presented in two distinct categories: low-stakes/formative, providing students with feedback, or high-stakes/summative, used to evaluate student learning at the end of a structured unit. The low-stakes formative assessments in the system are all optional, allowing the students to scroll by them and focus purely on the instructional content. These assessments consist of a variety of question types such as MCQs, short answer, and dropdown style questions. Each question in OLI is broken down into one or more problem steps, where each step corresponds to an opportunity for student input. For instance, if a question asks a student to set the value of three dropdown boxes, then it consists of three unique steps that each have their own set of feedback and correct or incorrect responses. This distinction between a problem and its steps is important, since students may work on a problem, but not complete all of the steps due to a number of reasons such as not knowing the answer to some of them, wanting to skip them to save time, or getting distracted (Chen et al., 2018).

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. Our data comes from the fall semester of 2020, when the introductory chemistry course was offered in the OLI system. In total, our data consists of 129 students, with 68 of them participating in the self-explanation activity.

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 dropdown, 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. Additionally, 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. Previous research using the OLI platform has found that students have varied participation levels with the optional activities found throughout the material (Moore et al., 2021). 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.

Data collection

We focus on an activity that was added to the course that involves each student generating a self-explanation as to why they chose their answer to a particular problem in the course. In the chemistry course, this activity is found in the second module of the content for this section of the course. This module provides several paragraphs of instructional text, two worked examples, and several low-stakes multiple-choice and short-answer questions on the topic of atomic mass. The self-explanation activity is presented in the same low-stakes and optional format as the other activities found throughout the course. In the activity (1), students are prompted to self-explain why they chose their answer to the short answer question above the prompt. The instructions for the self-explanation come from a related study by Asano et al. (2020) and are worded in a way to maintain the motivation of the student and briefly explain the concept of self-explanation. We intentionally wanted to keep this low-stakes and optional, to examine the students' participation with the task and the quality of their contribution.

Analysis

The student-generated explanations were coded by two experts to assess their quality and specificity. The two experts had content knowledge in chemistry and had ample previous experience coding qualitative student data. The inter-rater reliability was calculated and the Cronacbh'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; Menekse et al., 2011). Explanations were assigned scores from the rubric ranging from 0 to 4. The exact coding schema that was utilized by the two expert reviewers can be found at (2).

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 student used their knowledge of atomic mass and isotopes to determine the correct answer.

Results

Student participation and self-explanations

We found that over half of the students in the four courses wrote responses to the self-explanation task. In total there were 129 students in the instances of the course and 68 (52.71%) of them made a contribution to the self-explanation activity. The chemistry course used by all four instances consisted of 35 problems that were composed of 178 total steps. On average, students completed 22.66 problems ($SD = 14.67$) and 112.96 steps ($SD = 78.54$), meaning a majority of the activities were worked on by the students, despite being completely optional. A t-test showed a significant difference in the number of completed problems, $t(127) = 9.369, p < .0001,$ and steps, $t(127) = 9.319, p < .0001$, between students that did the self-explanation activity and those that did not do it.

The self-explanation task was in reference to a short-answer question found towards the beginning of the course that was completed by 83 (63.34%) of the 129 students. Even though 83 of the students completed the short-answer problem, only 68 of those students contributed to the self-explanation task. This means 15 students did the problem, but chose to not participate in the self-explanation. Additionally, students on average spent 99.82 ($SD = 82.99$) minutes actively working on the problems found in the course, meaning they were typing or had their cursor somewhere present in the activity box. The average time spent by students on the self-explanation activity was 103.58 seconds, with the least amount of time being 17 seconds and the greatest being 433 seconds.

Description and quality of student self-explanations

The self-explanations students provided were input into a multiline textbox that had an adjustable size, capable of fitting any length of text. On average, the student-provided self-explanations were 107.5 characters long, with the shortest response containing 1 character and the longest 363 characters. There was a significant and positive correlation between the amount of time a student spent on the self-explanation task and the length of their explanation, $r(67) = .28, p = 0.019$. This might suggest that students spent their time thinking and typing the explanation out for the task, rather than having their cursor idly on the activity. A Spearman's rank-order correlation test indicated that the time students spent working on the self-explanation task was also positively correlated with the rubric score they received for their explanation, $rs(67) = .26, p = .032$.

A summary of the rubric scores for the student self-explanations can be found in Table 1. There were 61 students (47.29%) who did not submit a self-explanation response. For the 68 self-explanations provided by students, a majority (66.18%) of them were scored as a 3 or 4, indicating they were relevant to the problem; some were general (score 3) while others were sufficiently detailed and specific (score 4) to the problem. The highest percentage of score 4 was found in the c2 course at 19.23% across all students in that instance of the course. However, a one-way ANOVA revealed there was no significant correlation between the four courses and the distributions of rubric scores in the range of 0-4 for student self-explanations, $F(3, 125) = 1.309, p = .274$.

Table 1 Distribution of the rubric scores assessing the quality of the self-explanations that students received across the four instances of the chemistry course.

			Rubric Score			
Course	0	1	2	3	4	**Total Students**
c1	30	3	2	15	7	57
c2	9	1	3	8	5	26
c3	12	3	3	2	3	23
c4	10	4	4	3	2	23
Total (%)	61 (47.29%)	11 (8.53%)	12 (9.30%)	28 (21.71%)	17 (13.18%)	129

Endnotes

(1) https://github.com/StevenJamesMoore/ICLS2022/blob/main/ICLS_2022_Figure_1.png
(2) https://github.com/StevenJamesMoore/ICLS2022/blob/main/ICLS_2022_Figure_2.png

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