International Society of the Learning Sciences

Who Writes Tomorrow's Learning Activities? Exploring Community College Student Participation in Learnersourcing

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Abstract: Generating multiple-choice questions (MCQs) is a popular form of learnersourcing that benefits both the students' higher-order thinking and the instructors' collection of assessment items. To better understand the type of students that engage with learnersourcing activities and inform whether these interventions are targeting all students or just a select few, we deployed multiple optional MCQ generation activities across three courses at two community colleges. To measure if these interventions were reaching all students, we analyzed how students' demographic data and performance in the course influenced their participation in a set of optional MCQ generation tasks. We found that students who performed better on the formative and summative assessments in the course contributed a greater number of learnersourcing activities; however, most of the top 10% of students in terms of quiz scores did not make any contributions, likely because they did not perceive these activities as necessary.

Introduction

Having students develop assessment questions has a long history as a learning activity, one that has shown real benefit in supporting student learning (Aflalo, 2018). These types of activities integrate deep engagement around subject matter with critical thinking and creative practices (Denny, 2015). Through the instrumentation of this process, student engagement can be leveraged in ways that provide meaningful data around student interaction, in addition to new student-generated learning assets that can support future learners (Denny et al., 2017). This is known as a form of learnersourcing, where students complete activities that produce content that can be leveraged by future learners (Kim, 2015). The continual creation and improvement of these questions allows for a greater breadth of topic coverage, helps to identify well-constructed and valid assessments, and as a result, enables improved learning opportunities.

While asking students to write new quiz or exam questions is a time-honored approach in many classrooms, current learnersourcing investigations emphasize the online context, where students' efforts to master domain content within a digital learning environment can be effectively studied at scale (Glassman et al., 2016). Specific implementation of learnersourcing activities can vary greatly between instructors, however, particularly in whether completion of these activities are treated as mandatory or optional (Moore et al., 2021). This distinction between mandatory and voluntary implementation is important: students who are offered a choice in completing learnersourcing tasks perceive these activities as having a greater value, gain more autonomy in the course, and contribute higher-quality questions compared to students that are required to participate (Singh et al., 2021). Indeed, efforts to force student engagement may backfire; requiring these tasks can lead to student disengagement as they participate with minimal effort in order to satisfy the requirements of the activity (Khosravi et al., 2021).

On the other hand, making the activities optional comes with its own risks: the activities may be neglected by the students who could benefit the most from these interventions, as oftentimes only the most driven students choose to participate in optional tasks (Inglis et al., 2011). This type of self-selection would have an impact beyond the individual students for learnersourcing activities, as only the top performing students may be generating data and new questions. This would in turn influence the question banks, hints, analytics, etc. generated by the students, limiting the diversity of the contributions, creating potential bias in the generated content, and potentially excluding a novice point of view that could be beneficial to learners (Nathan et al., 2001). Ideally students of all backgrounds and knowledge levels would participate in learnersourcing activities, but previous work has indicated otherwise – that participation for these question generation activities can be as low as less than 5% (Denny et al., 2018). These findings are further complicated by where such investigations take place, with a majority of the learnersourcing activities being deployed at top R1 four-year universities around the world (Wang et al., 2019).

Therefore, more research is needed to investigate which students are participating in these learnersourcing activities, how these interventions work and who they are targeting. To this end, we deployed several optional MCQ generation activities in three online courses across two community colleges in the United

States. Accompanying these tasks is a demographic survey to help better understand the students in the courses. As students worked throughout the first four or five weeks of their online course, they were presented with several opportunities to generate a MCQ for the given unit they were working through. We analyzed which students were participating and how their demographics and performance in the course may have influenced their participation. Our two research questions are as follows: (1) How does student participation with learnersourcing activities vary by student demographics? (2) How is student performance in the course related to their participation in optional learnersourcing activities? Through the investigation of these research questions, our work makes the following contributions towards online learning and learnersourcing tasks. First, we provide insights into the attributes of students that participate in learnersourcing activities. Second, we derive a set of performance measures commonly found in online courses that can serve as predictors of student participation in related activities.

Theoretical Framework

We research in a climate that has appropriately prioritized equity and brought the larger challenges of fairness and related ed-tech into sharper focus. In the context of learnersourcing, diverse student engagement is critical, not merely to support a research agenda, but also to expand learning materials to reflect the broadest possible student experience. In contextualizing this research, we first look at how student participation and performance in online courses are potentially influenced by their demographic background. We then detail the process of question generation as a learning activity and how these questions can be utilized. This approach works to prioritize students' prior knowledge as a critical input into the larger learnersourcing effort.

Online courses offer students different affordances compared to traditional in-person ones, which can be both beneficial and detrimental to learning depending on the student. A study by (Ruthotto et al., 2020) found that over 90% of the students enrolled in online computer science courses participated at least once, but overall participation rates ranged along a continuum from active to passive participation. They found that student participation within these courses varied by demographics, such as ethnicity and age. Particularly in STEM, evidence suggests that online courses can perpetuate enrollment and participation gaps for women or ethnicities that are traditionally underrepresented in these courses (Kizilcec & Halawa, 2015).

Student engagement with an online course can be defined by their participation in its learning activities (Gledson et al., 2021). Multiple studies have linked student performance to their engagement with the course materials, indicating that students who actively participate and do more activities have a higher chance to pass the course and receive a higher grade (Brunskill et al., 2018). While research supports the benefits of having students participate in optional activities found in online courses, other factors such as the demographics of the students may also influence their participation and ultimately their success in the course (Rizvi et al., 2019). For instance, student motivation in STEM courses can be affected by stereotype threat, causing a lack of a sense of belonging (Bathgate & Schunn, 2017). This lack of participation, particularly when it involves learnersourcing, presents several challenges that propagate throughout the course. When students have lower levels of participation, they do fewer activities, which can pose difficulties in modeling their learning (Long & Aleven, 2013). Students doing fewer activities also leads to less data being generated, which can hinder the efficacy of instructional interventions, such as recommending practice problems (Andrade et al., 2016).

Learnersourcing has been used in many online courses across a variety of domains, where students are typically tasked with generating questions, making hints, or providing feedback (Khosravi et al., 2021). Having students generate short answer or multiple-choice questions (MCQs) that can then be used as practice opportunities in the current or future courses is a particular focus of much learnersourcing research (Wang et al., 2019; Yeckehzaare et al., 2020). An obvious challenge that arises from optional activities is getting the students to participate with them and making a meaningful contribution (Carvalho et al., 2018). Previous research has demonstrated that completing optional course activities is strongly related to a student's performance in a course (Koedinger et al., 2015). As researchers and educators, we want students to participate in learnersourcing activities, given that such activities can provide useful learning data, contribute to the instructor's assessment question banks, and benefit student learning (Aflalo, 2018). However, it is important to understand what factors might influence students's decision to participate in these optional activities, as addressed in the study by (Singh et al., 2021). To determine if such activities are reaching all students in the course, or only those from the commonly represented demographics or top-performing group, we need to investigate these factors as they relate to students contributing to these learnersourcing tasks.

Methods

This study was conducted in three different courses at two 2-year community colleges located on the west coast of the United States. All three courses took place online during the fall 2021 semester and IRB approval was received for the survey and activities added to the courses. The three courses were introductory chemistry, advanced chemistry, and introductory statistics. The two chemistry courses were taught at the same community college, but by different instructors. Students taking introductory chemistry were required to have previously passed a course covering the topics of linear algebra. For the advanced chemistry course, students were required to have passed both a linear algebra course and an introductory chemistry course at the college-level. The statistics course was taught at a separate community college by a third instructor. The only prerequisite for students in that course was to have passed a college-level intermediate algebra course.

We utilize data that came from four to five week-long units that were used towards the beginning of each course. This data consists of student interactions in the course along with their performance on the quizzes found at the end of each unit. There were a total of 64 students across all three courses, who were taking the courses to receive credit towards their respective degrees. There were no students enrolled in both of the two chemistry courses. Table 1 shows the number of learners in each course, along with a breakdown of their self-reported gender, ethnicity, and first-gen status. It also includes the number of units, and therefore quizzes, in the respective course, as introductory chemistry had five units and advanced chemistry and introductory statistics had four units. Our demographic questions accepted free text input to allow students the highest flexibility in identifying their background.

Table 1

Breakdown of the students in each course, their demographic information, and the number of units

Course	Units	Students	Male	Female	First-gen	Hispanic/Latin	Asian	White
Introductory Chemistry	5	17	5	12	8	12	3	2
Advanced Chemistry	4	18	4	14	12	12	5	1
Introductory Statistics	4	29	6	23	19	15	6	8

All three courses were deployed on the same learning platform, known as the Open Learning Initiative (OLI), which has been used in previous studies involving online learning at community colleges (Bälter et al., 2018; Ryan et al., 2016). It contains functionalities akin to popular learning environments often utilized at universities or in MOOCs. Each unit in these courses was equivalent to a chapter in a textbook, consisting of five to ten related topics and taking up roughly one week to cover. The units contain multiple pages of instructional content featuring text and brief instructional videos. These webpages also host multiple low-stakes activities interspersed amongst the instructional content for students to use as practice opportunities. They include multiple-choice, short answer, essay, matching, and fill-in-the-blank style questions. All of these activities act as formative assessments, intended to provide students with instructional feedback. As such, they are completely optional and do not account for the students' grade in the course. Additionally, students may make any number of attempts on these activities, receiving instant feedback on their response with each attempt. In all three of the courses, each unit concludes with a summative assessment in the form of a quiz that tests students on the material covered in that unit. The quizzes consisted of only multiple-choice or fill-in-the-blank questions and ranged from 4 to 22 questions. Students' scores across all of the quizzes counted towards a low percentage (5-15%) of their final grade in the course. All student data collected from OLI is securely stored in accordance with its IRB approval. In addition to the OLI platform, students in these courses utilized a learning management system for the other parts of their course, such as submitting homework assignments or viewing announcement posts.

Data Collection and Analysis

Our dataset came from the four to five week-long units at the beginning of each course, with four primary components: 1) Demographic survey, 2) Formative assessments, 3) Summative assessments, 4) Learnersourcing activities.

Demographic Survey: When students first accessed the learning environment which hosts the formative and summative assessments, they were prompted with a brief demographic survey to complete. The survey asked the students to specify their gender identity, ethnicity, and if they were a first generational (first-gen) college student in their family. Students that did not fully complete this survey were not included in the present study. Additionally, as many of the responses were free-form, we had two researchers standardize the student responses (e.g., fixing typos), during this process there were no discordant cases.

Formative Assessments: Throughout each course there are multiple formative assessments, commonly referred to as problems, embedded amongst the instructional text and videos intended to provide the students with practice opportunities and immediate feedback. They consist of multiple-choice, short answer, essay, matching, and fill-in-the-blank style questions. These activities are optional and do not impact the student's grade in the course. Table 2 shows the total number of formative and summative assessments in each course – note that these do not include the count of the MCQ generation activities, which we describe below.

Summative Assessments: The end of each unit concludes with a page summarizing the content that was covered in the unit. This page also contains a link to the unit's quiz that students complete for a small percentage of their final grade. It consists only of multiple-choice and fill-in-the-blank style questions that can be automatically graded. In this study, the smallest quiz contains 4 questions, and the largest quiz contains 22 questions.

Learnersourcing Activities: At the end of each unit in each course, we placed a learnersourcing activity that prompts students to generate an MCQ targeting any concept they learned from the unit. The interface of the MCQ generation activity includes the brief instructions for the students[1]. The two bullet points shown in the activity's instructions reflect the unit's learning objectives which the MCQ should target. The number of MCQ generation activities is equal to the number of units in the course.

Table 2
The number of formative and summative (quizzes) assessments in each course

Course	Formative Assessments	Summative Assessments
Introductory Chemistry	126	5
Advanced Chemistry	94	4
Introductory Statistics	37	4

Our primary variable of interest is student participation with the learnersourcing activities in their respective course. In this study, we consider a student as having participated in the learnersourcing activity if they submitted a contribution that contains a question pertaining to the course's learning objectives, a correct answer choice, and three distractor options. If a student submitted a blank response, a random string of characters, or made no submission, they were not counted as having participated in the learnersourcing activity. Note that it was rare for students to exhibit this behavior, as the vast majority of them either skipped the learnersourcing activities or made an honest effort in their contribution to generate a MCQ. To measure student performance on the formative assessments, we used their accuracy on the first attempt they made on the problem. If they correctly answered the problem on their first attempt, then they would have the first-attempt correct for that problem. Previous research indicates that a student's first attempt at a problem is a strong indicator of their knowledge of the material (Corbett & Anderson, 1994). In the forthcoming analysis we utilize the average quiz scores of the students, as it represents their performance in the course up to that current point in the course.

Results

To understand which students were participating in the optional learnersourcing tasks, we first analyzed their demographic information in relation to their potential contributions to the learnersourcing activities. Next, we investigated the different patterns of student participation and performance by looking at their interactions with the formative and summative assessments embedded throughout the courses.

Student Demographics

[1] https://github.com/StevenJamesMoore/ISLS2023/blob/main/mcq_generation.pdf

In total, 37 of the 64 (*57.81%*) students participated in at least one of the learnersourcing activities in their respective courses. To further investigate student participation with the learnersourcing activities in the courses, we looked at the demographics for students that contributed to any of the MCQ generation tasks. A Fisher's exact test revealed that there was no statistically significant association between gender and participation with any of the learnersourcing activities ($p=.484$). Similarly, there was no significant association between first-gen status and student participation with the learnersourcing activities ($p=.794$). We also looked at participation on the tasks related to the students' self-reported ethnicity. A chi-square test of independence showed that there was no significant association between ethnicity and task participation, $X^2(2, N=64)=.27, p=.873$. Table 3 provides the count of students who participated in the learnersourcing activities in each demographic group.

Table 3
Student participation with any of the learnersourcing tasks and their demographic information

Participated in learnersourcing	Students	Male	Female	First-gen	Hispanic/Latin	Asian	White
Yes	37	9	28	26	23	7	7
No	27	6	21	18	17	6	4

For the 37 students that participated in at least one or more of the learnersourcing activities, we investigated if their demographic background had any statistically significant effect on the percentage of learnersourcing activities they completed. Note there were four learnersourcing opportunities in advanced chemistry and introductory statistics, and five opportunities in introductory chemistry. An unpaired two tailed t-test revealed that there was no significant effect of gender on the number of learnersourcing activities students worked on, $t(35)=.95, p=.348$, with females $(M=.59, SD=.09)$ doing slightly fewer of the learnersourcing activities than males $(M=69, SD=.10)$ on average. There was likewise no significant difference in the percentage of learnersourcing activities between first-gen students ($M=.62, SD=.08$) and others $(M=.61, SD=.13)$, $t(35)=-.12, p=.452$. A Kruskal-Wallis test was conducted to examine the differences of the students' self-reported ethnicity and the percentage of learnersourcing activities they completed. There was once again no significant differences in participation found between groups, $H(2)=0.516, p=.773$.

While students' demographic background had no significant association with their participation with the learnersourcing tasks or the amount of learnersourcing tasks they engaged with, we also looked at how this information might be associated with their overall performance and participation with the other material found throughout the course. We found no significant effect of gender on the percentage of other formative assessments done in the course, $t(62)=1.48, p=.144$, where males ($M=.54, SD=.11$) and females ($M=.41, SD=.09$) had similar participation levels. There was likewise no significant effect of gender on the average quiz scores, $t(62)=.61, p=.546$, with males ($M=.73, SD=.05$) and females ($M=.68, SD=.09$) receiving similar scores. Similar null effects were found for the formative assessments, $t(62)=-1.07, p=.287$, and quiz scores, $t(62)=-.83, p=.407$, between first-generation students ($M_{formative}=.46, SD_{formative}=.09; M_{quiz}=.71, SD_{quiz}=.07$) and others ($M_{formative}=.38, SD_{formative}=.11; M_{quiz}=.65, SD_{quiz}=.11$). Finally, a Kruskal-Wallis test revealed no significant formative assessment participation, $H(2)=3.913, p=.141$, or quiz scores, $H(2)=1.233, p=.539$, between students' self-reported ethnicities.

Student Performance

We focus on how student participation and performance within their respective course might reflect their contribution to the learnersourcing activities. Our study showed that students who participated in the learnersourcing activities ($M=.62, SD=.07$) had a significantly greater percentage of the formative assessments completed in their respective course than those that did not ($M=.18, SD=.02$), $t(62)=-8.07, p<.005$. Relatedly, there was a significant positive correlation between the percentage of formative assessments done by the students with the number of learnersourcing activities they completed, $r(62)=.28, p<.005$. Table 4 provides the average amount of formative assessments completed in each course by students who participated or did not participate in the learnersourcing activities, including those students that only did the quizzes in these averages.

Table 4

Average percentage of formative assessments completed in the courses and the average quiz scores, out of 100, by students that participated in the learnersourcing activity (Yes) and those that did not (No)

Course	Learnersourcing Participation			
	Average Percentage of Formative Assessments Completed		Average Quiz Scores (out of 100)	
	Yes	No	Yes	No
Introductory Chemistry	73.71	26.98	72.83	67.00
Advanced Chemistry	61.70	10.99	67.50	73.03
Introductory Statistics	49.83	22.45	64.23	71.27

While participation in the course was positively correlated with doing the learnersourcing activities, as expected, we wanted to further investigate if these activities were more likely to be done by students already performing highly in the course or if it was a true mix of the students. We found that students who performed better on the formative assessments in the course were also more likely to contribute to the learnersourcing activities. These students who participated in the learnersourcing activities (*M=.48, SD=.10*) compared to those who did not (*M=.66, SD=.03*) had a higher percentage of correctness on their first attempt in the formative assessments, $t(62)=2.99$, $p<.005$. For the 37 students that participated in one of the learnersourcing tasks, there was also a positive correlation between the number of learnersourcing activities completed and the percentage of correctness of first attempts on the formative assessments, $r(35)=.35$, $p<.005$.

Next, we examined student performance on the summative quizzes at the end of each unit. Table 4 also shows the average quiz scores across all three courses divided into two groups based on if the students participated in any of the learnersourcing activities. We analyzed how a student's performance on the quizzes correlated with the amount of learnersourcing activities they completed. Ultimately, we found a significant positive correlation between a student's average quiz score and the number of learnersourcing activities they did in the course, $r(s)=.26$, $p<.05$. Interestingly, across all three courses, seven students had a perfect quiz average, receiving full credit for all four or five quizzes depending on the course. However, of those seven students, only one of them participated in the learnersourcing activities, contributing to all four of them in the advanced chemistry course.

Discussion

In this study, we investigated how student demographics and performance within online community college courses influenced their participation in a learnersourcing activity that involves generating a multiple-choice question. We found that 37 of the 64 students across the three courses participated in at least one of the learnersourcing activities; these students came from a variety of demographic backgrounds, expressed in terms of self-reported gender, ethnicity, and first-gen status. Our analysis revealed a correlation between the completion of formative assessments and the likelihood of students participating and contributing to a higher number of learnersourcing activities. Interestingly, the top 10% of students, as determined by their quiz score averages, did not participate in any of the learnersourcing activities.

We found no significant relationships between the students' demographic background and their participation with the learnersourcing activities. This may in part be due to our students primarily reporting the same gender and ethnicity, thus decreasing the potential diversity of our sample. While we did not identify any significant effects, our data indicates that a majority of the students from all the reported ethnicities, genders, and first-generation status made at least one contribution to an optional learnersourcing task. While we were encouraged to see that students of all backgrounds were participating, learnersourcing research should continue to collect demographic information to ensure all students are being reached by the activities and interventions. A core benefit of learnersourcing student-generated questions is that their unique perspectives and backgrounds can be incorporated into the questions they create, ultimately avoiding expert-blindspot and contributing to a more diverse pool of questions (Nathan et al., 2001). However, if the learnersourcing activities are skipped by students, knowing why they are not participating in them and the backgrounds of those students, could potentially inform methods on how to better include all students.

As expected, due to prior research in the area, student participation with the formative assessments in the course was positively correlated with their performance on the summative assessments (Brunskill et al., 2018).

We found that students who did more of the formative assessment were also more likely to participate in the learnersourcing activities. There was also a strong positive correlation between the number of formative assessments done and the number of learnersourcing activities students completed. This further suggests students might follow a completionist approach when working through the online materials and not skip the learnersourcing activity, which has been previously reported by (Singh et al., 2021).

In addition, student performance on both the formative and summative assessments was found to correlate with participation and the number of learnersourcing activities completed. These results indicated that the highest performing students were skipping the task. As mentioned, 7 of the 64 students achieved a perfect score on all the quizzes in their respective courses, yet among these seven students, only one participated in the learnersourcing activities, doing all four offered in their advanced chemistry course. This brings into question if the optional presentation of the learnersourcing activities could be potentially excluding the lower performing students that might benefit the most from these interventions, as well as the top performing ones. While we seek to ideally find a middle ground and engage the full range of learners in the current study, such activities may potentially exclude both the most and least in-need students. The MCQs generated from these top students might be closer to the level of instructor ones due to the advanced domain knowledge they possess (Mitros, 2015).

Our contributions should be interpreted against the following limitations. The three community college courses used in this study feature students from three different self-reported ethnicities. While this is representative of the institution-wide demographics, courses at other community colleges might yield a different student population. Additionally, we focused our analysis on data from three STEM courses. Extending this research to more courses from other domains, including non-STEM ones, might provide a more representative sample of students. However, since previous learnersourcing work neglects to provide demographic information, our current focus provides a first step at investigating how the different student populations of a course might be contributing to learnersourcing tasks. Additionally, we did not ask the students to report their native language, which might influence students' willingness to participate in the MCQ generation process.

Conclusion

In this work, we investigated the optional participation of students in the form of learnersourcing, where they generated multiple-choice questions relevant to the course content. Across three community college courses, our results showed that student demographics had no significant effects on their participation with the learnersourcing activities. However, we had moderate participation from a wide range of students on the task across all courses. Our analysis suggests that students' likelihood of participation with a learnersourcing activity is more dependent on their participation and performance with the other assessments found in the course, rather than on their demographic background. Additionally, we identified several features of student performance in the courses that influenced their participation with learnersourcing activities. These findings demonstrated that better performing students were likely to participate in learnersourcing, yet students at the lowest and highest end of the performance spectrum may still neglect such activities. This work contributed the first study which explicitly investigates the demographics of students participating in learnersourcing activities. It demonstrates that optional learnersourcing activities can still garner participation from a diverse set of students. Future learnersourcing efforts may incorporate participation and performance analytics to encourage students to contribute to learnersourcing tasks.

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