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Board 15: Work in Progress: Mixing Flipped and Traditional Teaching to Support Conceptual Learning and Motivation in a Cell and Molecular Biology Course

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Work in Progress: Mixing Flipped and Traditional Teaching to Support Conceptual Learning and Motivation in a Cell and Molecular Biology Course

Historically, cell and molecular biology courses focus on memorization of facts through traditional lectures [1]. This approach is at odds with calls for integrative and applied learning outcomes [2] and has the potential to reduce student learning and motivation.

Pedagogical approaches such as Problem Solving Studio (PSS) and flipped course delivery have been previously shown to be effective at improving student learning and motivation [3]–[7]. In PSS courses, students work collaboratively to solve open-ended problems at a difficulty they are unlikely to be able to complete individually. The PSS instructor's role is to ask open-ended questions, help make student thinking explicit, and model questions that experts ask themselves while solving similar problems. The level of student support is modified in real time so students remain curious but not discouraged [3]. While fully PSS-designed courses have been shown to increase learning over a semester [3], incorporation of PSS within traditional lecture courses has not been documented. Additionally, publications on PSS have related to courses predominantly focused on mathematical modeling rather than the content typical of cell and molecular biology.

We implemented PSS as part of a set of course design changes in a required junior level biomedical engineering cell and molecular biology course. Our goals in doing so included improving overall learning, increasing student motivation, and enabling students to better connect factual information to engineering and societal challenges. We integrated PSS into 3-5 class sessions for three semesters. We are also flipping portions of the course to increase time for PSS and other active learning opportunities (current semester, data collection incomplete). This solution is more accessible to instructors given the time investment required to completely flip a course.

Our overall project goal is to determine effects of our instructional design changes on what and how students learn in the course. This Work in Progress paper addresses two initial research questions: RQ1. Does student learning increase over the semester, regardless of class type? RQ2. Does the class type (PSS or no PSS) affect concept inventory scores in this course?

Methods

Description of the course

Content in the course is typical of similar introductory engineering cell and molecular physiology courses. The course has two 75-minute course sessions per week. In Fall of 2022, three sessions were converted from lecture to PSS. Starting in Spring 2023, two additional course sessions were converted to PSS. The selection of sessions to change and problems for those sessions derived from informal observation of topics students struggled with in the original course. Faculty worked to create specific problems that related those topics to societal challenges in human health. For example, linking co-translational protein insertion and protein sorting in eukaryotes to cystic fibrosis patients.

Data collection

Data on learning come primarily from an existing cell and molecular biology concept inventory (CI) [8]. The CI contains 24 questions related to 9 learning goals in cell and molecular biology. Additionally, we collected data on motivation, demographic information, and exam grades for future analyses. CI and motivation data were collected using a pre-post design during the first week of classes and between the last course meeting and the final exam, outside of class time.

Data were de-identified and non-responsive data (i.e., no response questions for the CI) were removed. The final sample has CI data from 36 students with no PSS and 85 students in PSS semesters. The study was approved by our institute IRB (protocol number: H22015).

Analysis

For our Work in Progress research questions, we analyzed only the CI data and used a Classical Test Theory approach – i.e., totaling the number of correct answers as scores. Based on prior work using this CI, all incorrect responses were treated equally and items were scored for correctness. Scores were then totaled in two ways: first all CI items and, second, just items relevant to the PSS sessions in each course. Our analysis focuses on descriptive and significance testing of the PSS-relevant items. We also calculated the same scores using normalized learning gain (i.e., the percent of available improvement) to evaluate the impact of measurement ceiling effects on evaluating RQ1 and RQ2. We used a two-way ANOVA with interaction to separate the contribution of time (i.e., pre post) and pedagogy (i.e., PSS or non PSS) on each score.

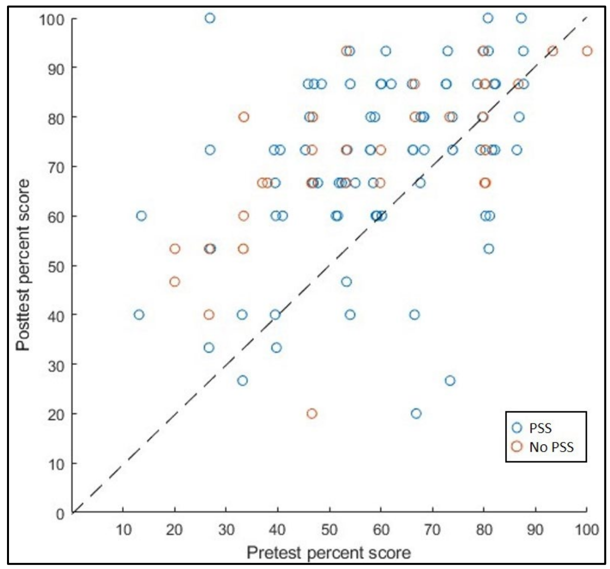

Figure 1. Paired pre- and post-course CI scores (with jittering). Points above the diagonal line indicate students who performed better on the post-course CI.

Results

As would be expected, all students' CI scores generally increased over the semester, regardless of whether the semester contained PSS sessions (Figure 1). From this analysis we also noted that students with higher pretest scores showed less gain. As noted in the methods, we suspect this phenomenon is due to measurement effects for this CI. We also evaluated the percent correct for each item (Appendix Figure 1). One item (1) had an overall very low percent correct compared to all others. We also noted items (e.g., 12) that had a high likelihood of correct response overall, and very little difference (i.e., learning) between pre- and post-course CI. We believe these are inducing some ceiling and floor effects on our measurements. We plan to address both in future semesters as well as in future analysis.

To address our second research question, we performed two-way ANOVA to test impact of class type (PSS or no PSS) and pre- and post-scores as well as their interaction (Figure 2). Our results show that the pre-post effect was significant (Δ_{mean}=1.83, $F(1,241)=24.53$, $p<.001$), but neither the class type (Δ_{mean}=0.36, $F(1,241)=6.42$, $p=.36$) nor the interaction of class type and pre-post were ($F(1,241)=4.01$, $p=.47$). That is, once

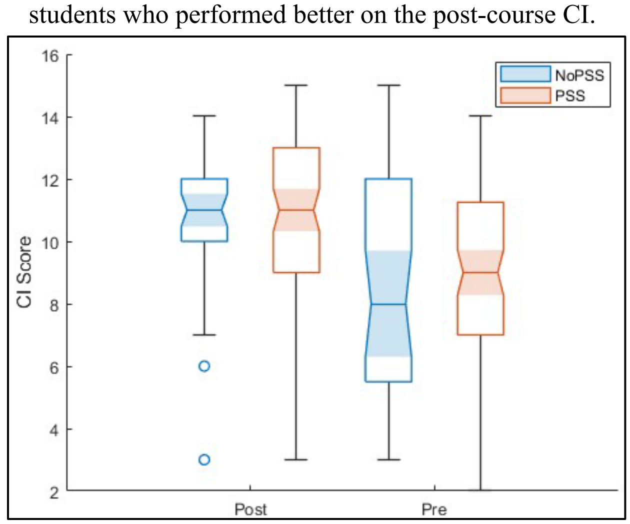

Figure 2. Box plot showing Two-way ANOVA of class type (No PSS vs. PSS) and pre- and post-course CI scores.

accounting for the overall pre-post change, there is no baseline difference between the PSS and non-PSS classes, which is useful. However, we also cannot conclude that class type had an effect on pre-post change in CI scores. Rather, the change in overall CI score across the semester seems independent of class type.

However, performing the same analysis using normalized learning gain (NLG) as opposed to raw CI score gave different results. Using NLG accounts for ceiling effects on our CI measure, i.e., students who scored very high on the pre-test have little margin for their learning to be measured by this CI. NLG is calculated as $\frac{(Score_{post}-Score_{pre})}{(15-Score_{pre})} * 100$. Surprisingly, the interpretation of the NLG ANOVA is not different from the raw score. However, plotting those results (Figure 3) shows the measurement ceiling, specifically multiple students with negative NLG.

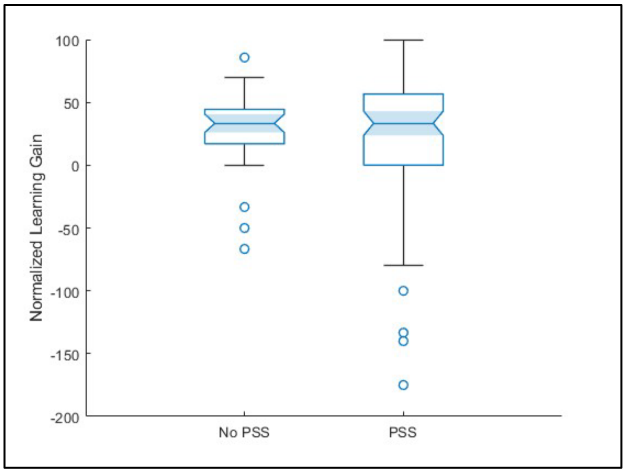

Figure 3. Box plot showing One-way ANOVA showing the effect of class type on normalized learning gain.

Discussion

Our analysis supported the expected outcome that CI scores increased over the semester in both class types. However, the analysis shows that the class type itself has no effect on the change in pre- and post-course CI scores – either raw or normalized for learning gain. Therefore, we concluded that student concept learning increased over the semester regardless of class type (RQ1), but that our current implementation of PSS does not affect CI scores (RQ2).

There are several limitations and other factors we plan to consider in the future. We observed that between pre- and post-CIs, scores only increased an average of 10%, which seems low compared to the improvements realized by students in the original CI study [8]. However, the overall CI scores, especially the pre-course scores, were higher for our students. Two factors may contribute to limitations in measuring the impact of our PSS. First, some students seem to enter our course with more prior knowledge, perhaps from recently taking a related class (or currently studying for the MCAT) whereas others last saw the material as a high school student, up to 6 years prior to the course. Students with more prior knowledge have little room for improvement and a higher chance of a test taking error, which can affect scores. Similarly, students may have spent little time or effort on the post-course CI. We observed instances of high scorers answering up to 7 more questions incorrectly on the post-course CI. Second, students could choose whether to register for the regular or redesigned course. Our findings may be limited by some extent to students who opted in to this teaching model (i.e., a non-randomized sample). We are also unable to use the standard PSS room structure of 4 students per table due to space constraints. Lastly, our analysis may show limitations of Classical Test Theory such as its reliance on total test score [9] and the potential for wide swings in item difficulty to reduce total score variance.

In future work, we plan to explore the how Item Response Theory may be used to draw conclusions from the data. We also plan to examine student gains beyond the technical content of the course by analyzing student responses to the MUSIC motivation inventory [10], [11], which was given simultaneously with the CI.

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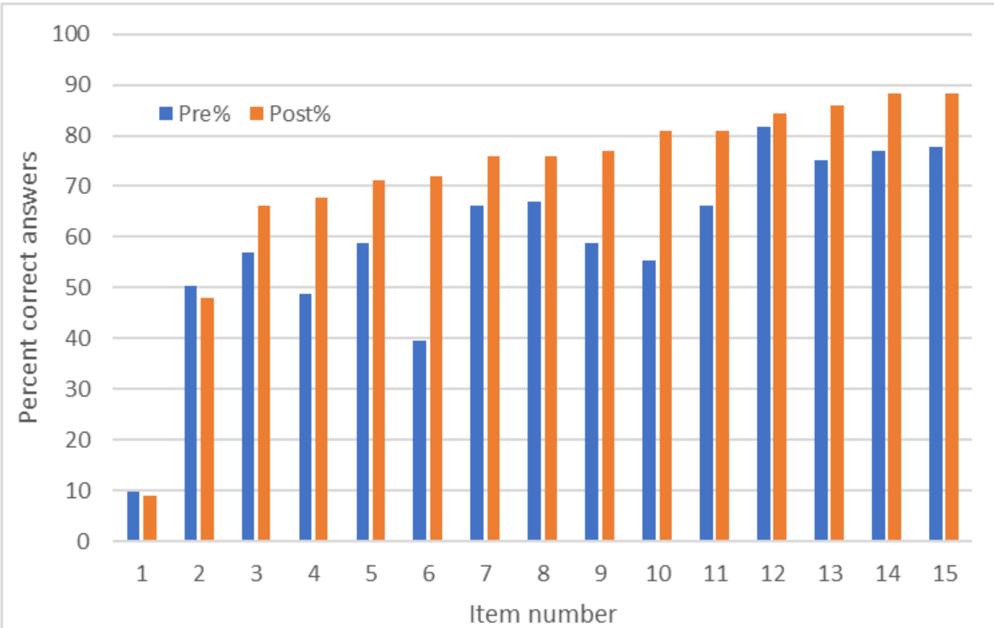
Appendix



Appendix Figure 1. The percent of correct responses on the pre- and post-course CI was determined for each question related to the PSS sessions, and sorted by post-CI percent correct.