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Comparing Different Learning Activities in a Global Neuroscience MOOC

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Work in Progress: Comparing Different Learning Activities in a Global Neuroscience MOOC

1. Introduction and Rationale

Massive Open Online Courses (MOOCs) attract learners from all over the world while offering unique opportunities and challenges. MOOCs are challenged to create a complete learning environment without a physical classroom or classroom resources[1,2]. *"Fundamentals of Neuroscience" (MCB80x),* offered by Harvard University, seeks to offer such a comprehensive learning experience by introducing interactive virtual labs and Do It Yourself (DIY) lab experiment videos in addition to lecture videos and a discussion forum. A small group of students were also sent at-home lab kits to further develop their understanding of the topic.

These activities fit the description of the activities in the Interactive-Constructive-Active-Passive (ICAP) framework, and thus student outcomes can be compared using their participation in these activities[3,4]. The ICAP framework has been used successfully to differentiate overt learning activities and explain differences in student outcomes by establishing specific and well-defined categories of learning activities[3,4]. In recent years, this framework has been used by Science, Technology, Engineering, and Math (STEM) researchers, who are trying to understand student learning not only in the classroom but also in online learning spaces. For example, Hasio and co-authors have used the ICAP framework to analyze discussion forum posts on online programming discussion forums[5]. In a previous study on student learning in a blended-learning MOOC, we used this framework to classify student activities and behaviors into all four categories[6]. Similar studies have used the ICAP framework to categorize student learning in face-to-face engineering classrooms. The results from this study indicate that students scored higher on the quizzes after participating in interactive and constructive activities. Moreover, the results of this study also show that student scores increased systematically from passive to active to constructive to interactive[7].

In this work-in-progress paper, we seek to understand the nature and effectiveness of student interaction with MCB80x. Two findings from our previous work are: 1) there was no significant bivariate correlation between the number of page views and student grades, and 2) there were numerous "outlier" students who had high interaction with the course website and either had a low grade or did not attempt the final exam[6]. Since there was no correlation between final grade and number of page views, we decided to analyze participation based on the type of activity completed instead of how much they interacted with the website. Thus, this paper classifies various activities performed by students of MCB80x into the four categories defined by the ICAP framework. As we continue to work on this study, we will use descriptive and inferential statistics to determine if student engagement in ICAP activities can be used to predict student success.

2. Theoretical Framework

As MCB80x provides a variety of engaging learning opportunities to its students, we use Chi's ICAP framework to inform our research question and to provide a schema with which we can categorize and explain our findings. This framework provides a hierarchical distinction between four types of learning activities: 1) INTERACTIVE learning activities support learners' peer-to-peer co-construction of knowledge, 2) CONSTRUCTIVE learning activities require learners to interpret existing learning content and generate new knowledge, 3) ACTIVE learning activities require learners to physically manipulate learning material, and 4) PASSIVE learning activities do not require learners to perform overt tasks[3,4].

3. Research Questions

To better understand the student experience vis-a-vis ICAP activities in this MOOC, this work-in-progress study asks two primary research questions:

1. Chi's main hypothesis is that the **I**nteractive activities are better, in terms of higher student learning outcomes, than **C**onstructive activities, **C**onstructive activities are better than **A**ctive activities, and **A**ctive activities are better than **P**assive activities. Is Chi's ICAP hypothesis supported in our context?
2. How does frequency of engagement in each ICAP activity type contribute to student grades in the course? For example, what types of activities did students with low total time in the course and high grades participate in most frequently? What activity types did those with the highest grades participate in more relative to those with the lowest grades?

4. Course Context, Data, and Sampling

This study focuses on the *"Fundamentals of Neuroscience" (MCB80x)* course*,* a MOOC offered by Harvard University using the edX platform. This neuroscience course provides a variety of activities including lectures, interactive videos, DIY videos, virtual labs, and supplemental materials. Student interaction with these resources was recorded from the start of the course (10/31/2013) until the end of the final exam (1/25/2014). The types of data initially collected by the online platform include: 1) student demographic information, 2) clickstream data, and 3) final exam grades. The clickstream data we have for this course can be sub-divided into different categories: 2a) the milestone dataset includes the start of each activity except for forum activity; 2b) the interaction dataset records every click the student makes within two different milestones on a certain screen control, e.g., for videos, this could be starting, pausing, zooming, or other associated activity; 2c) the login dataset records the time a student logs in to the course website; and 2d) the logout dataset records the time a student logs out of the course. An important point to note is that automatic logouts are not recorded in the data.

Over 24,000 students from 143 different countries enrolled in the 2013 offering of this course. A group of over 5000 students from this initial offering volunteered to participate in a Randomized Control Trial (RCT). The control group consisted of 4,978 students, whereas the treatment group consisted of 200 students. The students in the treatment group were sent at-home lab kits on which they could perform actual neuroscience experiments. Of the 200 students in the treatment group selected to receive the lab kits, 185 students actually received them. This work-in-progress paper focuses on analyzing the activities of this group of students. Since we are using the final exam grade as a measure of student success, we will be analyzing data from only those students who attempted the final exam (n = 49).

Thus, this work-in-progress seeks to categorize the activities in MCB80x and then categorize students by both the amount of time spent on these activities and their final grades. As given in the ICAP framework, our study differentiates between four kinds of learning activities: 1) Interactive, 2) Constructive, 3) Active, and 4) Passive. Students are also split into six different strata to begin to understand how each stratum's set of behaviors was related to differing outcomes. The stratification is done based on student grades and the time they spent on the website. The first level of stratification is done based on grade. We divide students first into two groups: students who passed and students who failed. Students who passed are then divided into high grades and low grades, as shown in Table 1. The range of grades and total times for each stratum is listed in Table 2.

Table 1. *Student Strata based on Grades and Total Time Spent in the Course*

Main Categories	*Grades*	*Total Time*	*Abbreviations*
Students who passed the final exam (score of > = 60%)	High Grades	High time spent in course	p_hi_hi
	High Grades	Low time spent in course	p_hi_lo
	Low Grades	High time spent in course	p_lo_hi
	Low Grades	Low time spent in course	p_lo_lo
Students who failed the final exam (score of < 60%)	High time spent in course		f_hi
	Low time spent in course		f_lo

Table 2. *Student Strata Grades and Total Times Ranges*

Strata	*Count*	*Grade Range (%)*	*Median Grade (%)*	*Total Time Range (min)*	*Median Time (min)*
p_hi_hi	10	78.62 – 89.86	83.15	1344.20 – 10751.62	2895.71
p_hi_lo	10	75.72 – 94.57	81.34	1.83 – 1322.52	691.55
p_lo_hi	10	60.51 – 73.55	66.67	827.93 – 6016.10	2187.57
p_lo_lo	10	60.87 – 71.38	64.86	189.95 – 795.6	354.48
f_hi	5	39.49 – 56.88	51.81	681.33 – 4562.85	990.23
f_lo	4	43.48 – 55.07	50.54	185.13 – 386.15	263.15

5. ICAP Activities in MCB80x

Activities in MCB80x were recorded as login times, page views, milestones, interactions, and logout times. Using the ICAP framework, we separated student activity into the four ICAP categories:

1. Interactive (I) activities are defined as peer-to-peer interaction that serves to deepen the student's understanding of the topic[3,4]. MCB80x's discussion forum best fit this activity type, as it was a place where students posted questions and discussions that were added on to by other students and the course instructors. Thus, it was an activity where information was co-constructed and fits the description of Interactive. The discussion forum data was used to calculate the amount of time students spent doing Interactive activities, as it was the only Interactive activity type in the course. Page view information was used to determine when students entered the discussion forum. Since our dataset does not record the exit time from the discussion forum, we calculate the total amount of interactive time as the difference between the time they entered the forum and a designated end time. Designated end time was determined as either the time of the next page view for that day or the time of the next logout, based on whichever came first. If

neither could be found for that day, the activity was recorded with an end time equal to its start time.

For Constructive, Active, and Passive activities, Milestone data (2a) provided the start times of each activity, and Interaction data (2b) provided the end times for the activity, where end times were defined as the time of last interaction. If there was no interaction, the end time for the activity was equal to its start time.

2. Constructive (C) activities are defined as tasks in which students generate or produce additional unguided output[3,4]. In the context of MCB80x, we identify two Constructive activities: student interaction with the virtual labs and DIY lab videos. Virtual labs allowed students to manipulate controls in order to determine how it would affect the formula/concept being studied. For instance, one virtual lab allowed students to manipulate the concentration of ions. The DIY lab videos showed students how to use the lab kit in order to perform experiments. Students of the treatment group are assumed to be working on their own personal lab kit while watching these videos. This study assumes that students were generating new and deeper knowledge of the concepts during their time spent on these activities.
3. Active (A) activities are defined as tasks where students manipulate their learning materials while engaging with the video content[3,4]. For this study, the active activities were those in which students interacted with the video controls while watching. It is assumed that by stopping and starting the video or rewinding, the student is manipulating the controls potentially to take notes or to better understand the material. This recorded manipulation of the video may show a greater likelihood of student engagement with the material. All videos had at least one interaction recorded just to start the video and another if they pressed stop. Thus, two interactions are potentially already recorded for each activity. To eliminate interactions that would not truly qualify as a student manipulating their learning materials, activities were counted as active if they had greater than 3 interactions (3 interactions = starting + stopping + one more click).
4. Passive (P) activities are those in which students passively absorb information[3,4]. The MCB80x activities that we categorize as Passive are: student interactions with lecture videos in which three or less interactions took place.

6. Student ICAP Behaviors

Using ICAP categories and student strata information, we aggregated the total time spent on each category for all students in the six strata defined above (Figure 1a). For each stratum, the time spent in each ICAP category was divided by the total time spent on all activities to show the percentage of time spent in each category (Figure 1b). To reiterate, strata in this study are defined as: passed(p) or failed(f) / low(low) or high(hi) grade / low(lo) or high(hi) activity, as shown in Table 1.

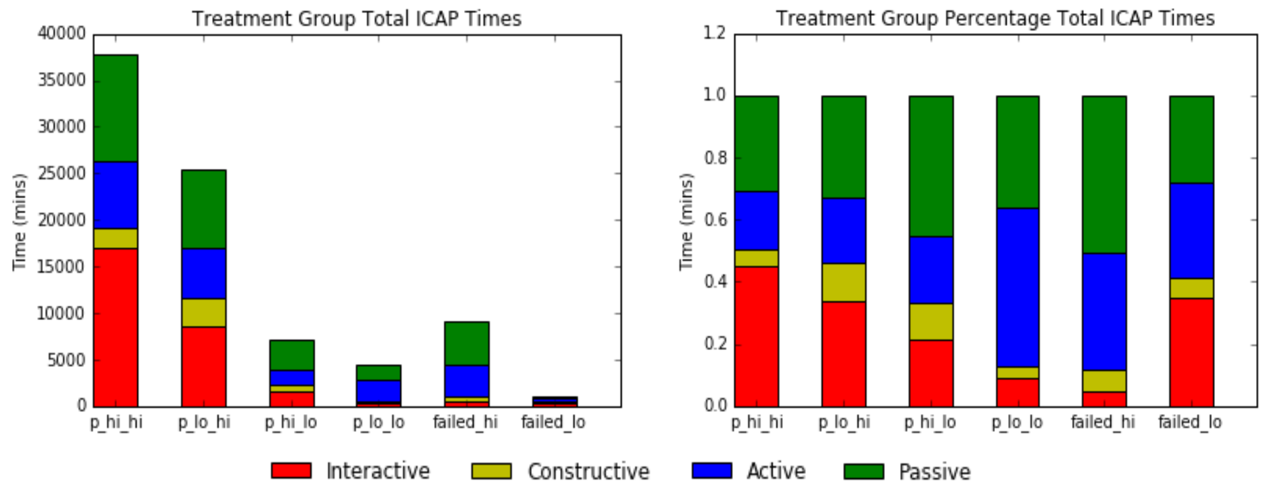

Figure 1a: *Total time spent on each type of ICAP activity for each student category*

Figure 1b: *Proportional ICAP time of total time spent on the course for each student category*

As shown in Figure 1(a & b) the students in the p_hi_hi strata spend more time engaging with all types of activities compared to the students in the p_lo_hi strata. Preliminary analysis suggests that students with high total time and high grades spent more time proportionally on interactive activities. This corresponds to the assertion of Chi's ICAP hypothesis that participation in Interactive activities leads to better student performance over all other types of activities.

The p_lo_lo and f_hi are two important groups to compare, because though the members f_hi group spent more time in the course than almost all of the p_lo_lo group members, the f_hi got lower grades. Thus, though time spent on activities did not significantly impact their grades, the types of activities they spent time on, may reveal the reason for the difference in grades. Figure 1(b) also shows that p_lo_lo and the f_hi students spent the majority of their time proportionally on active and passive activities and very little on constructive and interactive activities. While f_hi students spent more overall time on activities (Figure 1a), they spent almost equal amount of time on Active and Passive activities. Although p_lo_lo students spent less time on activities relative to f_hi students, p_lo_lo students focused more of their time on Active activities. This corresponds to the ICAP assertion that Active activities lead to better scores relative to Passive activities.

ICAP hypothesis is not supported by the activities observed by the p_hi_lo group as shown in Figure 1(a & b). This may be due to students' prior background in neuroscience. All students in this group reported on the survey that they were familiar with neuroscience, having either formal education in neuroscience in a college/university or being self-taught. Half of the p_hi_lo group currently teaches neuroscience. These student backgrounds may explain why their participation and final grades did not follow the ICAP hypothesis.

7. Future Directions and Limitations

Preliminary analysis suggests that students focusing more on interactive activities have higher grades compared to the students focusing on active and passive activities. Within the later group, students who focused more on active activities had a higher grade compared to students who focused primarily on passive activities. As an immediate next step, we will use descriptive and inferential statistics to answer the two research questions mentioned in this paper. We also aim to analyze the control group data using similar methods. We will then compare findings from the treatment and control groups to find differences in behavior based on the addition of the at-home lab kit as another constructive activity, which might explain potential differences in outcomes between treatment and control groups.

One limitation of this paper is the small sample size of the treatment group, who took the final exam. To test the ICAP hypothesis, we need an outcome variable which in this case is student grade. Hence, we can only include the students who took the final exam. Since the sample size is small, we cannot make any overarching conclusions about this group. Another limitation is that the quantitative data we have can only be used to analyze student behavior recorded in the clickstream data. Activities that took place externally (e.g., taking notes, interacting with the at-home lab-kit) were not recorded. For instance, lab videos, which were categorized as constructive, were assumed to indicate construction of knowledge with the lab-kit the treatment group received. However, from the clickstream data we are unable to discern if the lab-kit was being used by the student during this time.

As part of this ongoing study, we are also collecting qualitative data (interviews) from students who took MCB80x in Fall 2013 to understand how the students are interacting with the online and offline components of this MOOC. An in-depth understanding of student interaction with these activities will aid instructional designers in designing effective interactive and constructive activities, not just for MOOCs but also for other engineering and STEM blended learning courses.

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