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Preparation for Future Lockdowns: A Comparison of Student LMS Activity During and After COVID-19

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Abstract: We use CausalImpact analysis to compare student online activity during the COVID-19 pandemic, when all classes were online, and post-pandemic, when classes were offered in a mix of modes. Student activity was operationalized as activity logs from the Canvas Learning Management System (LMS). When compared with student activity in pandemic fully online classes, we found that, contrary to our hypotheses, student activity in post-pandemic fully online classes decreased while activity in post-pandemic fully onsite classes increased. We attribute the decrease in participation in fully online classes to factors such as Zoom fatigue and feelings of loneliness and prolonged isolation. The increase in student online activity in fully onsite classes might be explained by students' general preference for face-to-face interactions. They may have felt more connected to teachers and peers, leading to greater productivity overall. The discourse about the transition from online learning brought on by the pandemic is dominated by survey research. By examining student online activity in an LMS, this paper contributes an analysis of empirical data that supports the findings of prior studies about student perceptions of the online learning experience and their adjustments to the next normal.

Keywords: Learning Management Systems, COVID-19 Emergency Remote Teaching, CausalImpact

1. Introduction

In his keynote address during the International Conference for Computers in Education, Baker (2022) stated that, despite advances in analytics and data mining, the field still lacks theories "that could help build models robust to complexity and change. We still lack understanding of how change impacts models." We have learned that models perform less well when the conditions under which they are applied change (see "Algorithmic Bias in Education [Wiki]," n.d.). There are many possible causes of model degradation including changes in user interface design, differences in the way errors are counted, and differences in the learning population over the years (Baker, 2022).

When the COVID-19 pandemic forced schools to close in early 2020, many of the prediction models and detectors stopped being useful because some of the attributes that fed into them, e.g. student attendance data, were no longer being recorded or were recorded in different ways. As we emerge from the pandemic, educational systems have retained some of these new policies and formats, such as a greater openness to hybrid formats. In this next normal, can we still trust models that were built on pre-pandemic data? What value, if any, can we derive from data collected during the pandemic?

We argue that pandemic data still offers us value because it helps us anticipate the effects of lockdowns that may take place in the years to come. Climate change, new pandemics, civil unrest, and other factors may prompt educational systems to migrate online temporarily and the return to face-to-face formats later on. In this paper, we examine learning management system (LMS) activity from two time periods: during the pandemic, when all classes were online, and when most restrictions were lifted and classes were offered in a variety of formats. We use CausalImpact analysis (Brodersen et al., 2015) to determine differences in student LMS participation when all classes were fully online versus when they were offered in fully onsite, fully online, and variants of the two modes. We hypothesize that fully online student online participation will remain unchanged while student LMS participation for onsite classes and mixed-mode classes will decline.

2. Related Literature

As the pandemic waned, many studies emerged trying to assess the differences in learner perceptions of higher education teaching strategies, student course satisfaction, student intention to continue using e-learning platforms, and factors affecting student engagement. A study conducted at the University of Rajasthan in India (Sharma & Alvi, 2021) attempted to determine differences in student perceptions of various teaching methods before and during the pandemic. Using a questionnaire, they found that students had more positive opinions about pre-pandemic, blended e-learning formats than the purely web-based learning that they experienced during lockdown.

These findings were corroborated by the US-based study of Corral and Fronza (2022). They found that student course satisfaction declined when courses moved online. Student satisfaction ratings showed that satisfaction was high at the start of the pandemic. As the pandemic extended, though, both student satisfaction and engagement waned. They returned to normal levels when face-to-face classes resumed.

What accounts for the differences in satisfaction and engagement? Individual differences were key factors in overall satisfaction. Students whose learning preferences were compatible with distance learning and with sufficient technical resources and support services were more likely to have a more satisfying experience (Clary et al., 2022). Not all students enjoyed this level of compatibility. Many expressed that online learning was lonely and fostered feelings of laziness (Singh et al., 2021). Traditional learning, they said, made them feel more productive. Many had to cope with considerable "lifeload"—the sum of all pressures a student has to confront (Hews et al., 2022). Those experiencing external stresses engaged less than those who experienced greater well-being.

Moving forward, researchers found several types of student perceptions that influence students' intention to engage with distance learning again (Zacharis & Nikolopoulou, 2022). These included student perceptions of e-learning as enjoyable, that their time and effort lead to worthwhile outcomes, the adequacy of technical and institutional support, and the beliefs that important others such as peers and university mentors have about the students themselves.

The consensus from prior, recent research is that students are, in general, more satisfied with face-to-face formats than online formats. While this finding may be consistent with our own intuition and experience, all of these studies tended to rely on survey data. They queried students regarding their perceptions, but they could not offer empirical data about student online participation. This paper contributes to the discourse by analyzing student participation as represented by LMS activity.

3. Methodology

3.1 Dataset Preprocessing

This study makes use of Canvas LMS log files collected from a university in Quezon City, Metro Manila, Philippines during the Summer period of Academic Years (AY) 2021-2022 and 2022-2023, which serve as the pre-intervention period and the post-intervention period respectively. This is because the classes during Summer of AY 2021-2022 were all fully online as opposed to the mixed-modality nature of Summer of AY 2022-2023. In addition, the list of courses offered during the Summer of AY 2021-2022 and AY 2022-2023 were similar to each other. The Summer of AY 2021-2022 ran from June 28, 2021 to August 6, 2021 (LS One Student Blueboard, 2021) while the Summer of AY 2022-2023 ran from June 13, 2022 to July 23, 2022 (Ateneo de Manila University Loyola Schools, 2022). The Canvas logs were first trimmed down so that only the logs that were generated by the 6,519 students and 737 teachers who were present in both Summer of AY 2021-2022 and Summer of AY 2022-2023 are included, and then are tallied overall per date, role type (students or teachers), and class ID, regardless of the event type each log pertains to.

In addition to the Canvas log files, this study also made use of two datasets, one for the Summer of AY 2021-2022 and another for the Summer of AY 2022-2023, containing the list of courses, their sections with their respective Canvas Class IDs, and the learning modality used for the Summer of AY 2022-2023, which includes the following:

- Fully Online - All class activities were conducted online during all class days (J. Sugay, personal communication, November 17, 2022).
- Hybrid - Some class days were for online class activities, and others were for onsite class activities, for the entire class (J. Sugay, personal communication, November 17, 2022).
- Flex - All class activities included students who were onsite and online at the same time during all class days (J. Sugay, personal communication, November 17, 2022).
- Online+ - Most class activities were online with the exception of special activities (such as exams, presentations, laboratory sessions, etc.) which were onsite (J. Sugay, personal communication, November 17, 2022).
- Fully Onsite - All class activities were onsite (face-to-face classes) during all class days.

In order to simplify the assumptions, we only included courses offered during both Summer of AY 2021-2022 and Summer of AY 2022-2023. Furthermore, all sections of any given course offered during Summer of AY 2022-2023 had to follow the same modality.

One of the critical decisions we had to make was the choice of pre-intervention dataset. As mentioned earlier, we had five post-intervention cases: Fully Online, Hybrid, Flex, Online+, and Fully Onsite. The post-intervention dataset for each of these courses was composed of data from all classes offered in these modes. We decided that the pre-intervention dataset of each of these cases would be composed of the same courses offered during the pandemic. To illustrate, suppose that the following were the courses offered during the pandemic and post-pandemic periods as shown in Table 1.

Table 1. *Courses Offered During the Pandemic and Post-Pandemic Periods (Illustration)*

Pandemic Courses (All Online)	Post-Pandemic Courses	Post-Pandemic Modality
A	A’	Fully Online
B	B’	Fully Online
C	C’	Hybrid
D	D’	Flex
E	E’	Online+
F	F’	Fully Onsite
G	G’	Fully Onsite
H	H’	Flex
I	I’	Hybrid
J	J’	Online+

The pre-intervention and post-intervention datasets would therefore be as shown in Table 2.

Table 2. *Pre-Intervention and Post-Intervention Datasets Based on Table 1 (Illustration)*

Post-Pandemic Modality	Pre-Intervention Dataset	Post-Intervention Dataset
Fully Online	A, B	A’, B’
Hybrid	C, I	C’, I’
Flex	D, H	D’, H’

Online+	E, J	E', J'
Fully Onsite	F, G	F', G'

Note that for this analysis, we did not take into consideration the differences between courses, nor the differences in course contents. The final breakdown of the number of courses and their respective number of sections/classes studied are shown in Table 3.

Table 3. *Breakdown of the Number of Courses Analyzed and Their Classes*

Modality	Total Courses	Total Classes (2021)	Total Classes (2022)
Fully Online	74	126	133
Hybrid	33	66	50
Flex	4	8	5
Online+	9	17	17
Fully Onsite	2	2	2

The aggregated Canvas logs and the list of courses were then split according to the academic period. For each academic period, the list of courses was first merged into the aggregated Canvas logs. Then, the resulting dataset was again aggregated according to date, user type, and modality. The total number of classes per modality for the academic period (see Total Classes (2021) and Total Classes (2022) columns in Table 3) was obtained from the list of courses, and was divided from the total number of logs calculated according to date, user type, and modality, and then discretized using a ceiling function to get the average number of logs per class for that date, user type, and modality. Lastly, the t-column represents the number of days elapsed. The values for the Summer period of AY 2021-2022 are computed by subtracting each date d from August 7, 2021, the day after the last day of Summer AY 2021-2022 (LS One Student Blueboard, 2021). The values for the Summer period of AY 2022-2023 are computed by subtracting each date d from June 13, 2022, the first day of Summer AY 2022-2023 (Ateneo de Manila University Loyola Schools, 2022). The t-column therefore has negative values for the Summer period of AY 2021-2022, 0 for June 13, 2022, and positive values for the Summer period of AY 2022-2023. The datasets were then appended back together, then split into separate CSV files (10 in total) according to user type and modality in preparation for CausalImpact analysis using R. Prior to the analysis proper, we take one plus the absolute value of the lowest negative t-column value (that is, pertaining to the first day of Summer period of AY 2021-2022, which is June 28, 2021) (LS One Student Blueboard, 2021), and add it to all of the t-column values in order to conform with the requirement in CausalImpact that t-values need to be positive, continuous, and chronological.

3.2 CausalImpact Analysis

For each modality, CausalImpact was performed with the student data as the outcome variable and the teacher data as the predictor variable. CausalImpact is a type of causal inference that estimates the impact of an intervention (e.g. transition from fully online classes to a variety of learning modalities) using Bayesian structural time series models (Brodersen, 2014; Brodersen et al., 2015; Lagmay & Rodrigo, 2022). Furthermore, in contrast to some other popular causal inference methods like Interrupted Time Series or Prophet (further explained in (Lagmay & Rodrigo, 2022) alongside other alternatives), CausalImpact offers both better predictions and easier interpretations (Kuromiya et al., 2020), although one limitation of it is that it is "only able to observe the outcomes under the treatment for one time series and under the control for the treatment for another one, but not the potential outcome under control for the former and under treatment for the latter" (Li & Bühlmann, 2020). CausalImpact takes in the predictor and outcome variables, as well as the pre- and post-intervention time segments in order to model the relationship between the predictor and outcome variables using the pre-intervention data, estimate the post-intervention counterfactual, and give the impact of the intervention by measuring the difference between the counterfactual and the observed post-intervention data (Lagmay & Rodrigo, 2022).

We used the teacher data as the predictor variable following the Teacher Expectancy Effect or Pygmalion Effect which states that teacher expectations have an impact on students' academic performance (Szumski & Karwowski, 2019). A lengthier discussion for our rationale is available in (Lagmay & Rodrigo, 2022). The period pertaining to Summer AY 2021-2022 was designated as the pre-intervention period, while Summer AY 2022-2023 was the post-intervention period.

4. Results and Discussion

4.1 Basic Statistical and Descriptive Analysis

Figures 1 and 2 show the overall average number of logs per class generated by students and teachers, respectively, per modality type and time period, in order to illustrate the difference in LMS usage behavior by user type and modality. For the students data, only the classes using the Fully Onsite modality experienced an increase in the average number of Canvas logs per class (95.54%). This is despite the fact that average teacher activity for the same classes decreased by -29.62%. In contrast, teacher activity in the Flex and Online+ classes saw an increase of 4.93% and 47.88%, respectively.

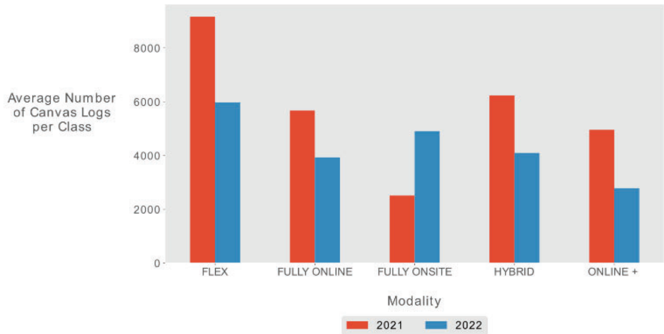

Figure 1. Overall Average Number of Logs per Class Generated by Students.

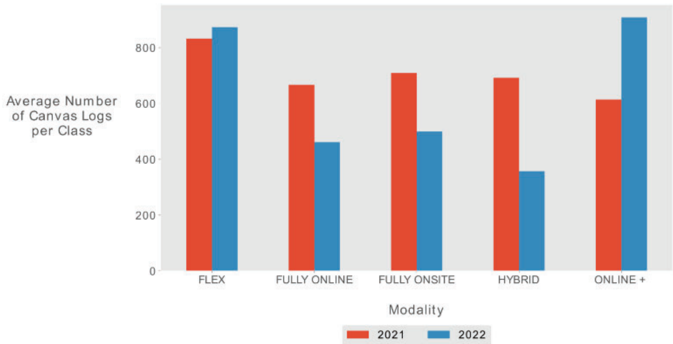

Figure 2. Overall Average Number of Logs per Class Generated by Teachers.

4.2 Fully Online Classes (Control Group)

Figure 3 shows that the average number of logs per class for Fully Online classes significantly decreased during the Summer of AY 2022-2023 with p = 0.014. An explanation of the graphs shown in Figures 3 to 7 is as follows:

"Each unit on the x-axis represents one day in the time period. The topmost graph labeled "original" shows a solid line representing the actual observed data, i.e., the number of transactions per day. The broken line represents the prediction. The light blue band represents the confidence interval of the prediction. The middle graph labeled "pointwise" shows the difference between the predicted number of transactions and the actual number of transactions per day….Finally, the cumulative graph at the bottom shows the accumulated difference between the predicted number of transactions and the actual number of transactions….The [vertical gray dashed line] is the intervention [time]. There is no accumulated difference during the pre-intervention period. The differences are accumulated post-intervention." (Lagmay & Rodrigo, 2022)

The average value obtained was 98.70 as opposed to the counterfactual prediction of 115.28. The overall estimated effect was -16.58 with a 95% confidence interval of [-31.83, -1.78]. When the data points during the intervention period are summed, the response variable had an overall value of 3,950, as opposed to the counterfactual prediction of 4,610 with a 95% interval of [4,020, 5,220]. Average Canvas logs per class decreased by -14% with a 95% confidence interval of [-24%, -2%].

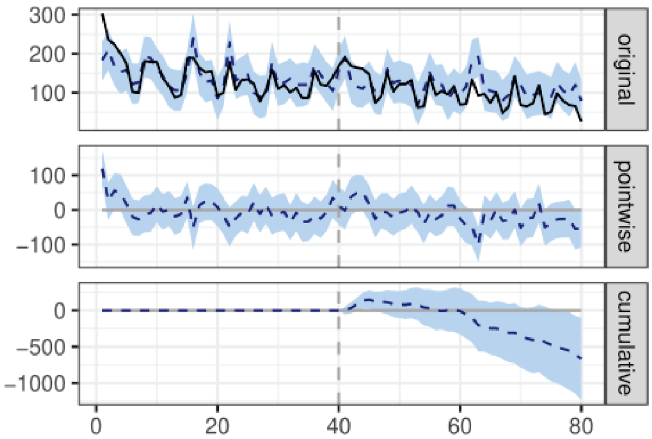

Figure 3. CausalImpact Graph for Fully Online Classes.

4.3 Hybrid Classes (Experimental Group 1)

Figure 4 shows that the average number of logs per class for Hybrid classes decreased during the Summer of AY 2022-2023, but not significantly. The average value obtained was 102.83 as opposed to the counterfactual prediction of 117.57. The overall estimated effect was -14.74 with a 95% confidence interval of [-35.91, 5.68]. When the data points during the intervention period are summed, the response variable had an overall value of 4,110, as opposed to the counterfactual prediction of 4,700 with a 95% interval of [3,890, 5,550]. Average Canvas logs per class decreased by -12% with a 95% confidence interval of [-26%, +6%]. The difference in the signs meant that the decrease with p = 0.07 was not significant.

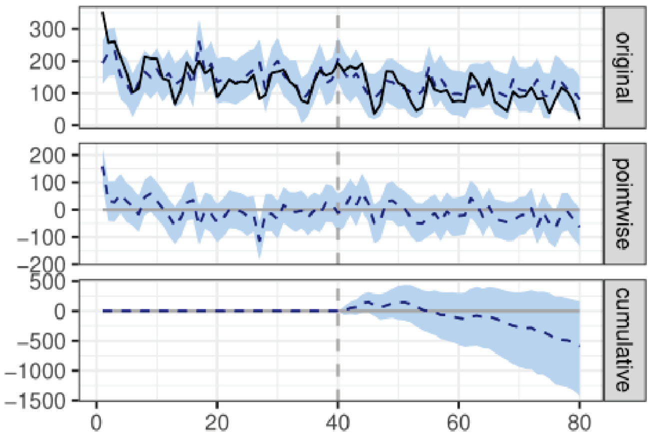

Figure 4. CausalImpact Graph for Hybrid Classes.

4.4 Flex Classes (Experimental Group 2)

Figure 5 shows that the average number of logs per class for Flex classes significantly decreased during the Summer of AY 2022-2023 with p = 0.001. The average value obtained was 149.68 as opposed to the counterfactual prediction of 227.76. The overall estimated effect was -78.09 with a 95% confidence interval of [-113.40, -43.26]. When the data points during the intervention period are summed, the response variable had an overall value of 5,990, as opposed to the counterfactual prediction of 9,110 with a 95% interval of [7,720, 10,520]. Average Canvas logs per class decreased by -34% with a 95% confidence interval of [-43%, -22%].

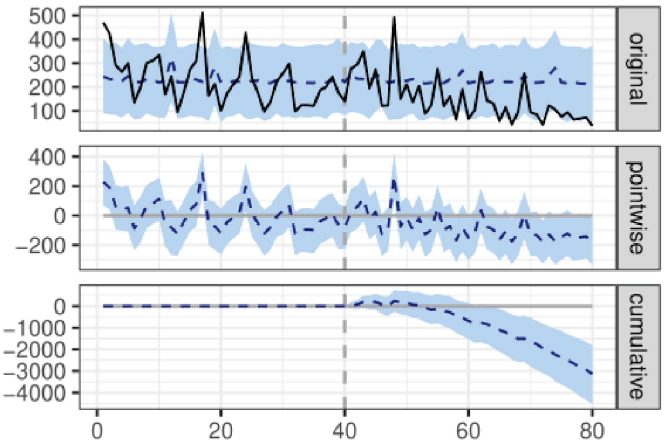

Figure 5. CausalImpact Graph for Flex Classes.

4.5 Online+ (Experimental Group 3)

Figure 6 shows that the average number of logs per class for Online+ classes significantly decreased during the Summer of AY 2022-2023 with p = 0.001. The average value obtained was 69.85 as opposed to the counterfactual prediction of 137.58. The overall estimated effect was -67.73 with a 95% confidence interval of [-86.15, -51.62]. When the data points during the intervention period are summed, the response variable had an overall value of 2,790, as opposed to the counterfactual prediction of 5,500 with a 95% interval of [4,860, 6,240]. Average Canvas logs per class decreased by -49% with a 95% confidence interval of [-55%, -42%].

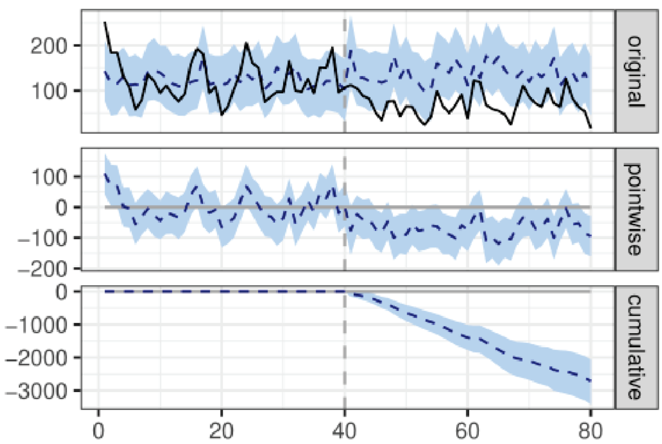

Figure 6. CausalImpact Graph for Online+ Classes.

4.6 Fully Onsite Classes (Experimental Group 4)

Figure 7 shows that the average number of logs per class for Fully Onsite classes significantly increased during the Summer of AY 2022-2023 with p = 0.001. The average value obtained was 122.88 as opposed to the counterfactual prediction of 57.44. The overall estimated effect was 65.43 with a 95% confidence interval of [49.51, 80.58]. When the data points during the intervention period are summed, the response variable had an overall value of 4,920, as opposed to the counterfactual prediction of 2,300 with a 95% interval of [1,690, 2,930]. Average Canvas logs per class increased by +117% with a 95% confidence interval of [+67%, +191%].

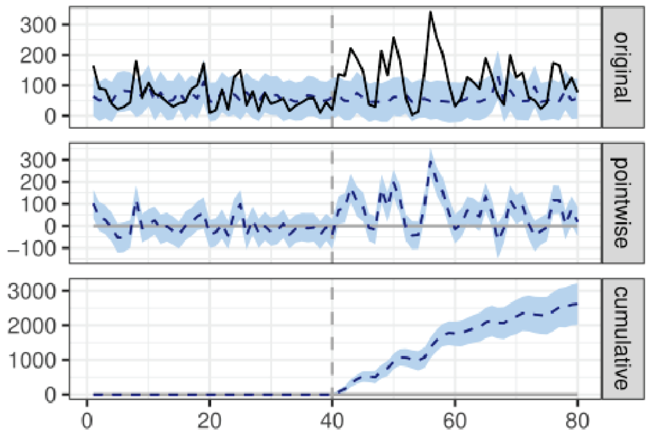

Figure 7. CausalImpact Graph for Fully Onsite Classes.

5. Conclusion

We used CausalImpact analysis to examine differences in student LMS participation when all classes were Fully Online versus when they were offered in Fully Onsite, Fully Online, Hybrid, Flex, and Online+ modes. We hypothesized that fully online student online participation would remain unchanged and that participation in all other modes would decline. As hypothesized, online participation in Flex and Online+ classes declined while online participation in Hybrid classes did not differ significantly from activity in pandemic fully online classes. What was surprising though was that participation in Fully Online classes declined while online participation in Fully Onsite classes increased, and these are the findings we would like to unpack further.

From prior literature, we draw several possible explanations for these outcomes. As mentioned in the review of literature, students generally were unsatisfied with the online learning format. They found it isolating and lonely (Singh et al., 2021). They much preferred face-to-face classes or modes that mixed online and onsite formats (Sharma & Alvi, 2021). They suffered "Zoom fatigue" and lacked interactions with peers and mentors (Corral & Fronza, 2022). Working online made them feel less productive (Singh et al., 2021). Furthermore, classes that were purely asynchronous made students feel less capable of understanding course content (Hews et al., 2022). To continue online meant to continue to experience these feelings, all of which may have diminished interest and engagement.

When given the opportunity to work onsite, students felt more productive (Singh et al., 2021). They said that in-person classes with teacher and peers contributed to greater focus and engagement (Hews et al., 2022). They could ask questions as these arose.

The main limitation of this study is that it relies purely on LMS data. It does not have any survey data or qualitative feedback that might help explain the results, and we did not consider the differences among courses nor the learning design utilized by the courses. While references to prior work are useful, the populations across all these studies are different and therefore differences in student experiences may exist. Future work should attempt to collect and analyze more qualitative feedback to weave a fuller narrative explaining pandemic versus post-pandemic student online activity. Also, a more fine-grained analysis such that the logs are aggregated according to event type (e.g. assignments, quizzes, etc.) should be considered in order to determine which specific parts of the LMS actually increased or decreased depending on the modality.

The other limitation is that the study does not capture the case where students were enrolled in classes with different modalities. Many students had a mix of onsite, online, and mixed-mode classes, and the impact of this intermingling on their overall participation and engagement was not considered in this analysis. In addition, we did not consider the possibility that some students may have failed a course and had to retake it, which may also affect the results. However, such data is not readily available from the Canvas log files alone. Lastly, this study did not take into consideration previous studies on fully online and hybrid courses prior to the pandemic, and as well studies related to the development of digital skills which may help further explain the results.

Despite these limitations, this study contributes to the discourse in at least three ways. It offers an analysis of empirical data from an underrepresented country. It illustrates quantitatively how student participation changed from the pandemic to the post-pandemic period. These changes are a cue to data scientists to think about how to build more robust models that generalize in the fact of major events such as COVID-19. Overall, the findings give educators insight as to what to expect when the next lockdown occurs, and how we might better prepare and recover from it.

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