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Title: The transition back to in-person university classes during the coronavirus disease 2019 pandemic: an agent-based modelling study

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Reviewer 1: Dr. Affan Shoukat **Institution:** Yale University

General comments (author response inbold)

In this study, the authors utilize an ABM to evaluate timetables for undergraduate students returning to university. The results are of the study are expected (i.e. lower contacts -> lower number of infections).However, I do have a few questions.

One issue with returning back to university is the large number of contacts in and out of lecture halls. Students will naturally mingle amongst friends, gather together for food, and engage in other social activities. As a consequence, any benefits gained from a specialized schedule/timetable will quickly erode. I am now wondering if it is possible to consider a strategy where students stay in one lecture hall(and surrounding area for social gathering/breaks) rather than movingabout the university to different lecture halls? In this strategy, the professors will travel from room to room providing lectures instead ofstudents switching lecture halls. This will make contact tracing easier should there be an infection.

This sounds like an excellent idea. For our model we consider interactions within hallways during class changes and also consider outside transmission of the virus. Wherever possible, I would suspect institutions would try different strategies to minimize student contacts between classes such as single lecture halls (as suggested) and directed traffic in hallways (e.g., floor markings). Ourmodel will likely result in more virus spread because of interactions in hallways between classes; however, this should not have a major impact the relative efficacy of different timetabling policies.

I am wondering about model calibration and what exactly the transmission rate was. How was the transmission rate adjusted for presymptomatic and asymptomatic individuals. How was the transmission adjusted for outside transmission. Was there a probability that each individual could be infected (due to interactionat their household) before attending an in-person lecture?

We have added a section on validation to Appendix A (appendicespp. 9-11) where we describe the process used to calibrate and validate our model. The process involved performing a number of tests to investigate the model's operational validity.

The in-class transmission rate is based on the non-household secondary attack rate taken from the meta-analysis by Koh et al. (2020). We use the ratio of symptomatic vs. asymptomatic secondary attack rate from this study to adjust for asymptomatic contacts.

Both of these numbers are used to determine the probability that each individual could be infected due to interactionsin classes.

The outside transmission rate (cases/100,000/week) was used to determine the probability of outside transmission for the cohort of180 students. This number was taken from the Government of Alberta and Government of Canada COVID-19 reports. We have re-run our experiments with the current outside transmission rate (which is considerably higher than the outside transmission rate atthe time when our first set of experiments were performed).

The changes to Appendix A involved replacing Figure A.2 (appendices p. 10) with a more detailed figure showing the number of students susceptible, infected, and recovered over time. As well, we added Table A.2 (appendices p. 11) to provide sensitivity analysisresults. As part of the sensitivity analysis, we looked at variations in the outside transmission rate. The model does show somesensitivity to this parameter.

Reviewer 2: Dr. Kelsey Spence **Institution:** Public Health Agency of Canada

General comments (author response inbold)

The authors present a modelling study describing the impact of various timetabling methods on reducing outbreaks of SARS-CoV-2 among students. They conclude that a combination of sustained non-pharmaceutical interventions (e.g. contact tracing) and smaller, less- frequent, in-person classes was the most effective strategy at reducing outbreak size.

In general, the paper is interesting and very well written. The authors clearly explained the rationale for the study and provided good supporting evidence of using an engineering cohort given the importance of in-person skills building for accreditation. One suggestion that would improve the clarity of the paper is perhaps a sentence or two in the methods describing the timetabling options. Itis described in the appendix, but it would allow readers to easily see which interventions were tested without referring to the appendix. Similarly, perhaps clearly stating which of the timetabling methods was the “best” in the abstract/interpretation session would help inform readers of the most optimal strategy to use.

We have included additional information on the timetabling optionsin the “Methods” section. As well, we have provided more information in the captions for Table 2 (text p. 8 and p. 15) and Figure 2 (text p. 7 and p. 18) to help the reader interpret the convention used for describing the timetabling options.

I have a few comments about the model. It seems, based on the appendix, that this was a network-based model. I think that is appropriate given the use of timetabling, but further details should beprovided on how contacts were assigned – e.g. completely at random,using a small-world algorithm, spatial allocation in a classroom, or certain number of connections? Also, were these contacts assumed tobe stable over time in a given timetable session? I would also like to see some discussion of the impact of physical distancing on contacts –it is likely that any transition back to in-person learning will use masksand appropriate physical distancing (if possible) so that might impact the results.

Thank you for these comments on the structure of the model. We have added material to the "Entities, States, and Variables" section of Appendix A (appendices pp. 1-2) to describe the relationship between student agents. The distance between students (i.e., the closeness of their personal relationships) are assigned randomly at the start of each simulation run and are assumed to be constant over the run (i.e., the 12.7 week term). The timetabling cohorts are established at the start of each simulation run by dividing the students evenly between the cohorts and assigning students to eachcohort based on their proximity to each other. The assumption here is that "close relationships" are primarily related to students sharingthe same classes; however, the random placement of students in thesimulation world view results in some relationships to be closer thanothers (e.g., through friendships and shared interests) and opportunities for cross cohort interactions (e.g., in hallways between classes).

We did not directly consider the impact of social distancing or the use of masks in the model. This would definitely be of interest in future versions of the model. Although these interventions would beused in real classroom situations, we took the view that they would have a consistent impact across all scenarios (i.e., reducing the secondary attack rate) and as a result, the relative difference between timetabling scenarios would be consistent with rates used in our model.

Similarly, for the contact tracing intervention, what proportion of contacts are assumed to be identified by students? Analysis of community contact tracing data shows that cases cannot recall contacts with 100% accuracy, so it would likely overestimate the effectiveness if all contacts were traced and isolated. At any point arecontacts quarantined before becoming symptomatic?

In our model, we have assumed that students recall a maximum of 10 most recent contacts (this is represented by the "tracing depth" variable in the model). We agree that students cannot recall contacts with 100% accuracy and that this can lead to overestimatesof the effectiveness of contact tracing. To check this, we performed a sensitivity analysis of the tracing depth parameter and did see a slight decrease in the mean number of students infected as tracing depth was varied from 2 contacts to 10 contacts. However, the difference in the results caused by varying the tracing depth was very small compared to the difference between no contact tracing (symptoms-based surveillance) and contact tracing (even when onlyusing the 2 most recent contacts). We have added the results of thissensitivity analysis to Appendix A (appendices p. 11).

In Table 1, it isn't always clear how the parameter values are translated into the model. For example, how do the attack rate, secondary attack rate, and asymptomatic attack rate impact the probability of transmission? Is the "test duration" the time to test results, and what happens while a student is waiting for the results(e.g. do they go to class still?). What impact does the outside transmission rate have on the attack rate within the school?

A new table, Table A.1 (appendices p. 4), and a short description hasbeen provided in Appendix A to describe how the parameter estimates from Table 1 were incorporated in the model. We have also provided additional text in the "Model Overview" section on these parameters (text p. 5).

The outside transmission rate (cases/100,000/week) was used to determine the probability of outside transmission for the cohort of180 students. This number was taken from the Government of Alberta and Government of Canada COVID-19 reports. We have re-run our experiments with the current outside transmission rate (which is considerably higher than the outside transmission rate atthe time when our first set of experiments were performed).

In the appendix, it is mentioned that the observations are assumed to be normally distributed, but I would ask the authors tocheck the distribution of their results to assess whether the use of non-parametric statistical methods would be more appropriate.

This assumption was used to estimate the number of simulation replications needed to achieve a desired 95% confidence interval width for our main output measure (number of student infected). We made this assumption based on the Central Limit Theorem: i.e., given that this output measure is the result of the combination of many independent random variables it should tend toward a normaldistribution. For our experiments, we targeted a 95% confidence interval with a width of 5%. Our simulation results appear to fall within this width: e.g., the Table 2 results have 95% CI widths in the range of 3.3% to 7.6%.

Lastly, a minor comment about consistency – in some areas, the authors refer to the pathogen (SARS-CoV-2) and the disease (COVID- 19) interchangeably, this could be distinguished in the introduction and then one or the other can be used for the remainder of the paper.

Thanks for this comment. We have updated the paper to refer toCOVID-19.