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# COVID-19, Crowdedness, and CMC Dining: An Agent-Based Model Approach to Reducing the Spread of COVID-19[†]

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**Abstract.** To make a COVID-safe return to in-person learning in the fall 2021 semester, Claremont McKenna College (CMC) created a new outdoor dining option to decrease the number of students inside the dining hall at one time: food trucks. However, crowding often occurs at both the inside and outside dining options. And so, we constructed an Agent-Based Model (ABM) to simulate the flow of students to the dining options over the lunch time hours. We use our ABM to investigate when over the lunch period crowding occurs and how often both or either option is crowded. Our analysis examines three different student behaviors namely, the ability to stick to an initial preference, the ability to sense crowding, and the ability to be influenced by other students. We find that the behavior that influences the level of crowding in the dining areas the most is having a strong preference for one of the dining areas. We also explore two different control measures that CMC could take to reduce crowding: adding another outdoor food option or increasing the amount of grab-and-go options. We find that adding another dining area is more effective in reducing crowding.

## 1. Introduction.

When COVID-19 swept across the globe in 2020, it left society with a fear of crowds. COVID-19 is an air-borne virus that spreads through sneezing, coughing, or simply breathing when an infected person is in close-contact with another person [8]. As scientists learned more about how the virus spreads, businesses and institutions began to introduce social-distancing measures aimed at reducing the amount of time people spend in close proximity. The Claremont Colleges have worked hard to create a safe return to in-person learning, but because of the high level of interactions that take place in the college environment, they have struggled to balance COVID safety with students' desire for a "normal" college experience. The biggest areas of concern are the dining halls; it would be impossible to have safe social distancing if students congregated in the halls at pre-COVID levels. Thus, the different colleges created ways to address this problem. One of the Claremont Colleges, Claremont McKenna College (CMC), added an outdoor dining option—food trucks—in an attempt to reduce crowding at its main dining hall, Collins Dining Hall (Collins). But some questions remain. Is this strategy effective? Does this new option spread out the number of students at the dining options well enough during dining hours? If so, is it effective for the whole time students eat at the dining options or just some of it?

The goal of this study is to answer these questions using an Agent-Based Model (ABM) of CMC students at lunchtime, defined as the midday hours between 11 am and 2 pm. For this study, we wanted to chose a time that both dining options are available (CMC only has food trucks for lunch and dinner) and that the largest amount of students use CMC's dining options opposed to going off campus, cooking for themselves, etc.

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This is why we chose to exam the lunchtime hours. Additionally, since the vast majority of students get out of class around 12:30 pm creating a high density of students at the dining options, investigating this time allows us look into how this dining strategy works against a high percentage of the CMC student population.

To embody the dynamics seen at CMC's dining options, our model must recognize that not all students act similarly. We studied previous research to add this dimension to our model. In an ABM designed to represent how people make decisions on whether or not to drink alcohol Gorman et al. created three different groups for three different behavior streams [5]. We used the same methodology to parse the students into different dining preference groups: students who prefer Collins, students who prefer the food trucks, and a final group of students who make an initial decision of where to eat based on the closest dining hall, but can be influenced by other students going to the other dining option. This third category of students is very important, as it represents how people's decisions change as they are influenced by external factors.

We drew upon research done by G. Rindsfüser and F. Klügl to create the student influence in our ABM. Their study examined crowding in a railway station in Switzerland to suggest infrastructure and scheduling changes to mitigate crowding [10]. The researchers explain how traditional techniques present pedestrian flow as large-scale, aggregate "flows;" however, this "flow" model doesn't take into account individual pedestrian interaction. This information led us to choose an ABM over other types of mathematical models, since ABMs can model agents that act independently instead of as an aggregate. Using an ABM allows us to include interactions between our agents that influence an individual's lunchtime dining decisions. The "run in" effect is central to our model due to the nature of the CMC campus, where other students often run into each other on their way to lunch. Our ABM design enables us to simulate this important component of students' decisions about whether to go to Collins or to the food trucks.

Another important component of our model is students' ability to "sense" crowdedness. We drew on the El Farol ABM to create this aspect of our model [6]. The El Farol bar problem represents a scenario where agents must choose to attend a bar or not based on their prediction of whether it will be too crowded to be enjoyable. Unlike the El Farol model, our model does not require students to predict attendance, as they have the ability to go to the area surrounding the dining halls and "see" if it is too crowded to enter. This aspect is crucial to our analysis since it allows us to examine how student behavior changes in response to the crowdedness level of the dining options.

The purpose of our model is to explore two questions, the first being: which behavior is most influential in affecting crowding? To answer this, we create several versions of the model, adding a layer of complexity in each version. We start with a first version of the model that consists only of students with a preset preference for either Collins or the food trucks. Then, we create a second version in which we gave those two groups the ability to sense crowdedness. Our third version adds a third category of students with no pre-set preference who are able to be "influenced" but cannot sense crowdedness. In this third version, the other two groups of students can still sense crowdedness. The fourth version, what we call our base model, allows this third group to both be influenced and sense crowdedness. We isolate these behaviors so that we can explore both the level and length of crowdedness in the dining halls for each extension; this allows us to see whether "influenceability" or crowdedness-sensing has a larger effect on levels of crowdedness in the dining halls.

This brings us to our second question: how can we reduce crowdedness in the dining halls? Specifically, we propose adding a third food truck or other outside dining option. In addition, we simulate possible changes to CMC's dining options to hypothesize control measures for reducing crowdedness and how long dining options are crowded for. Our analysis looks at when and how long each dining option is crowded for; what we call the level and length of crowdedness, in order to determine which of the proposed control measures is more effective in reducing crowding.

The paper is organized as follows. Our methods are in section 2, an explanation of the different versions of the model is in section 3, analysis and results are in section 4, and the conclusions follow in section 5. For a detailed explanation of how we created the model following the ODD Protocol see Appendix A.

## 2. Methods.

**2.1. Summary.** Our ABM illustrates the CMC student dining experience over the lunch period during the Fall 2021 semester. The basic building blocks of our model are as follows: the student population, the Collins dining hall area (along with the area that is adjacent to the dining hall), and the food trucks (which are treated like one entity), along with the area that is adjacent to the food trucks, and the general CMC campus area. Our analysis focuses on tracking when there are too many students at either of the dining options and for how long those dining options are crowded for. Crowding is defined to occur when attendance at either of the food areas reached 60% of its total capacity. We used data given to us by CMC's food preparation company, Bon Appetit, about daily lunchtime attendance at the dining halls to calculate the total capacity at Collins and the food trucks. For a more thorough discussion of how we calculated total capacity, see Appendix A.5. Sixty percent was chosen as it is the standard crowding threshold for similar models, such as the El Farol model or Minority Game problem [6] [7]. We use our analysis to uncover if there is a way to optimize the dining options so that there are never too many students during lunchtime, given student dining preferences, schedules, and the power of peer influence. Thus, our ABM collects data on where students decide to go, where students are congregating over the lunch period, and where there is crowding (if there is crowding at Collins and/or the food trucks).

**2.2. Assumptions.** One of the most important assumptions that we make in this model is that all the measures the food trucks and Collins are undertaking are not only sufficient for mitigating the spread of COVID-19, but are followed to the point that they are effective, so that keeping everything else constant, crowding would be the only factor that would increase the spread of COVID-19. In terms of model mechanics, we presume that crowding is reached when 60% or more of the dining area's student capacity is breached. Using meal delivery apps to get Collins to-go is not included in the model in order to focus on the most popular lunchtime options. Other food locations on campus are excluded in this analysis as well. From inspecting a data sample of the number of students that go to the Hub for lunchtime is only about 6-8 people a day. Considering the size of the CMC student body, this number is insignificant enough so that we exclude the Hub from our lunchtime dining options. Although there are cases of CMC students eating off-campus, cooking by themselves, getting into other dining halls, having their friends get them food from other dining halls, or students from other nearby colleges in the Claremont Consortium sneaking into Collins/food trucks, we also do not include these irregularities in the model because of their negligible amount. A few students stay inside of Collins from the breakfast period (since the employees at the dining hall allow them to stay and there is a 30 minutes between breakfast hours and lunch hours), but this amount is an extremely small percentage of the student body, and so is excluded from the model. For the purposes of understanding the basics of the crowd dynamics we would like to study, we assume that each person in our model is a CMC student and enters/swipes their student ID by themselves for themselves only. For the Overview, Design concepts, and Details (ODD), please see Appendix A.

**3. Versions and Control Measures.** This section explains how we created the different versions of our model, as well as the control measures. Our model was created incrementally with four versions with the first version being the most simplistic one and the fourth version being the most realistic version and, hence, acting as our base model. We then introduced two other models that built on our base model by adding a control measure each to the problem of overcrowding.

| Model Name | Summary |
|---|---|
| Version 1 | Two groups of students;<br>red group has pre-set preference for Collins,<br>green for the food trucks.<br>They cannot sense crowdedness. |
| Version 2 | Two groups of students;<br>both groups can sense how<br>crowded a dining area is.<br>Students can change their lunch location<br>if their preferred option is too crowded. |
| Version 3 | Three groups of students;<br>the third, new group begins with a preference<br>for the eating area closest to them and can change their<br>preference if they are "influenced by"<br>(touch) a red or green student.<br>This blue group cannot sense crowdedness;<br>once influenced, they go straight to their new preference.<br>Note: red and green students can still sense crowdedness. |
| Base Model | Three groups of students;<br>blue, red, and green students now all have the<br>ability to sense how crowded the dining areas are.<br>Only blue students have the ability to be influenced. |
| New Food Control Measure | Extends the Base Model by adding a new category<br>of students colored black that begins with a pre-set preference<br>to go to a new food source. |
| Eating Duration Control Measure | Three groups of students;<br>the only change in this model from the Base Model<br>is to change the distribution of the time that students<br>spend eating so that students on average<br>spend less time eating in the dining areas. |

**Table 1**
*Summary Table of Different Model Variations*

Version 1 of the model has two groups of students. Each group has a preferred dining option with the first group preferring to go to Collins during lunch while the second group prefers to go the food trucks. When the timer starts, both groups go to their preferred locations. The students in this model do not sense how crowded the dining location is before they enter. They simply enter the location and leave when their duration of eating elapses.

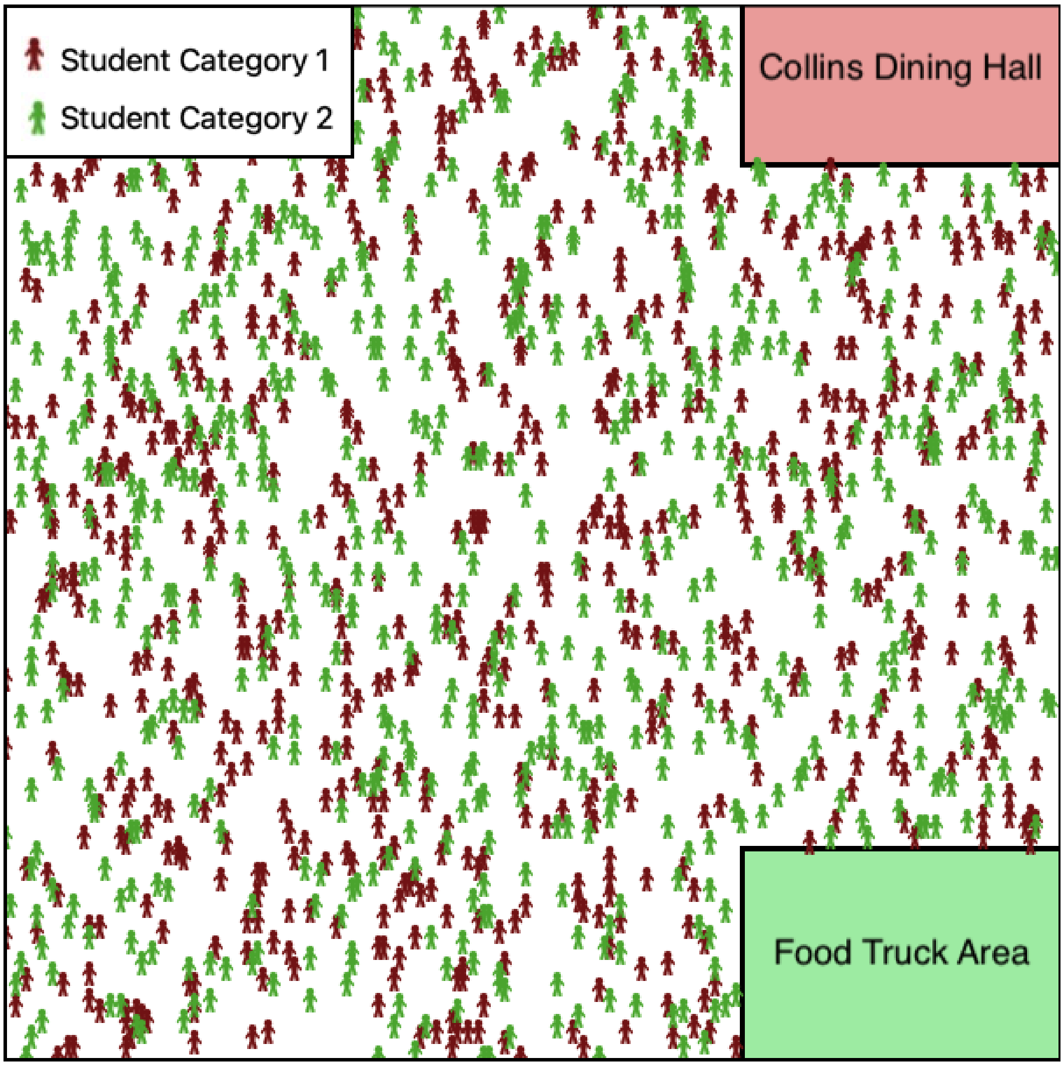



**Figure 1.** *Model setup for Version 1 which has two student categories. Each category has a set dining location. Each category of student goes directly to their dining location during the lunch period.*

Version 2 of the model adds the ability for both groups of students in Version 1 to sense how crowded the dining locations are before they enter. Since both groups are able to sense how crowded the dining locations are, they know when the locations are overcrowded provided they are close enough to sense crowding. Overcrowding occurs when the number of people inside the eating location is greater than or equal to the crowding threshold set for that location. More on how crowd sensing is done and how the thresholds are set can be found in Appendix A.

In both groups, if they sense that the dining location is overcrowded they change their preferred eating option to the other location. For example, a turtle which goes to the Collins Dining hall patches and finds that it is overcrowded will change its eating preference to the food trucks and will move towards the food trucks instead.

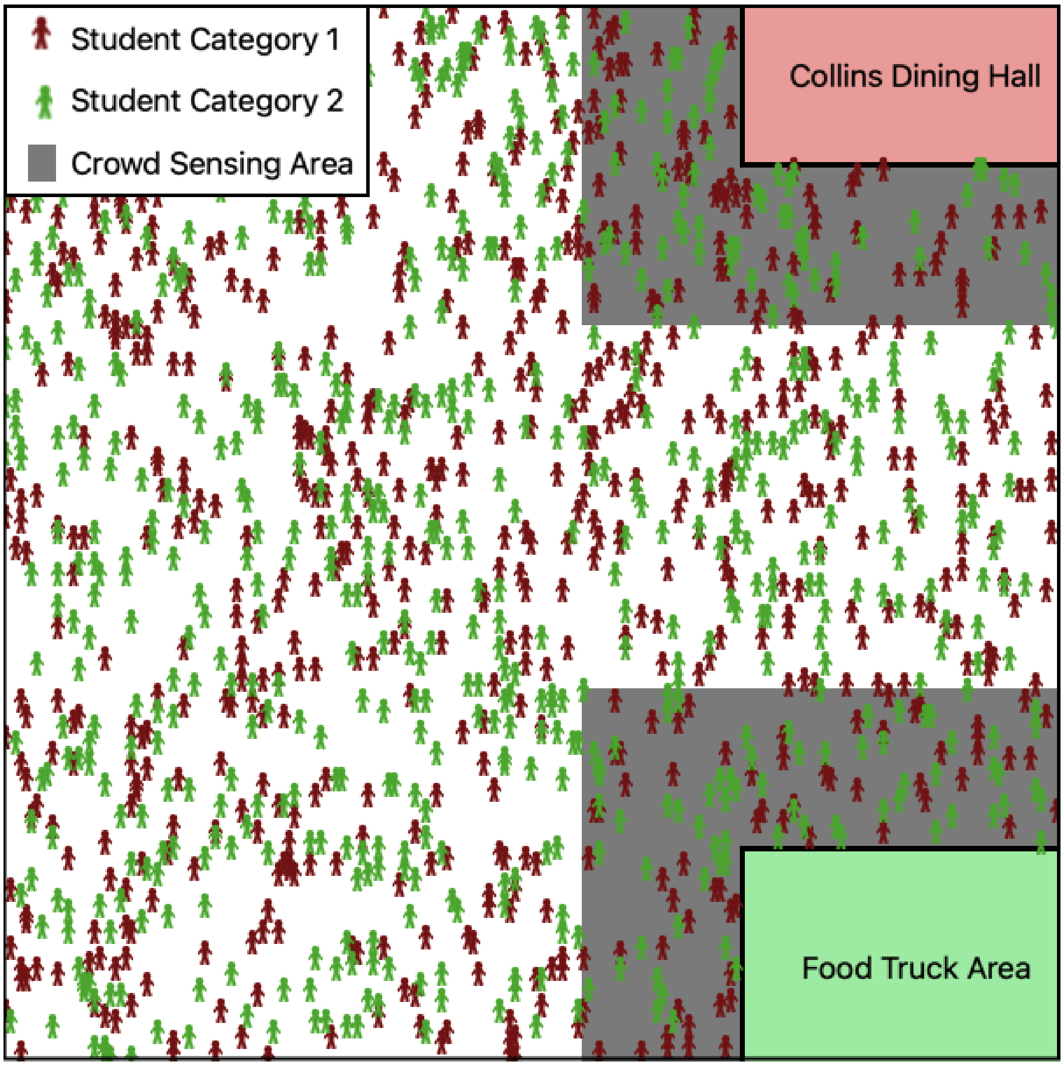



**Figure 2.** *Model setup for Version 2 which adds a crowd sensing area (in gray). When students get into the crowd sensing area, they are able to tell approximately how many students are in the dining area with increasing accuracy as they get closer. If the area is too crowded, they switch their dining location to the other dining option.*

Version 3 of the model builds on Version 2 by adding a third group of students who are colored blue and whose preferred eating location can be influenced as they interact with other students. Students in this third group start the model with their preferred eating as the location that is closest to them. As they pursue their eating option, they interact i.e., touch other students. When a blue student interacts with another student who is not colored blue for the first time, they are influenced by that student. They change color from blue to the color of the student they were influenced by and they also change their preferred eating location to that of the student they interacted with. Thus, through these interactions, the students in the third group can be influenced on their way to the dining hall. It is important to note that students who get influenced in this model are not yet able to sense crowding for themselves. Essentially, once a student is influenced, they go to their new dining option no matter how crowded it is. It is also important to note that students who get influenced cannot be influenced a second time.

The fourth version of our model, which we also call our Base Model in this paper, is very similar to Version 3. The only difference is that students who get influenced can also sense crowding on their own and hence can change their new dining options based on how crowded that location is.

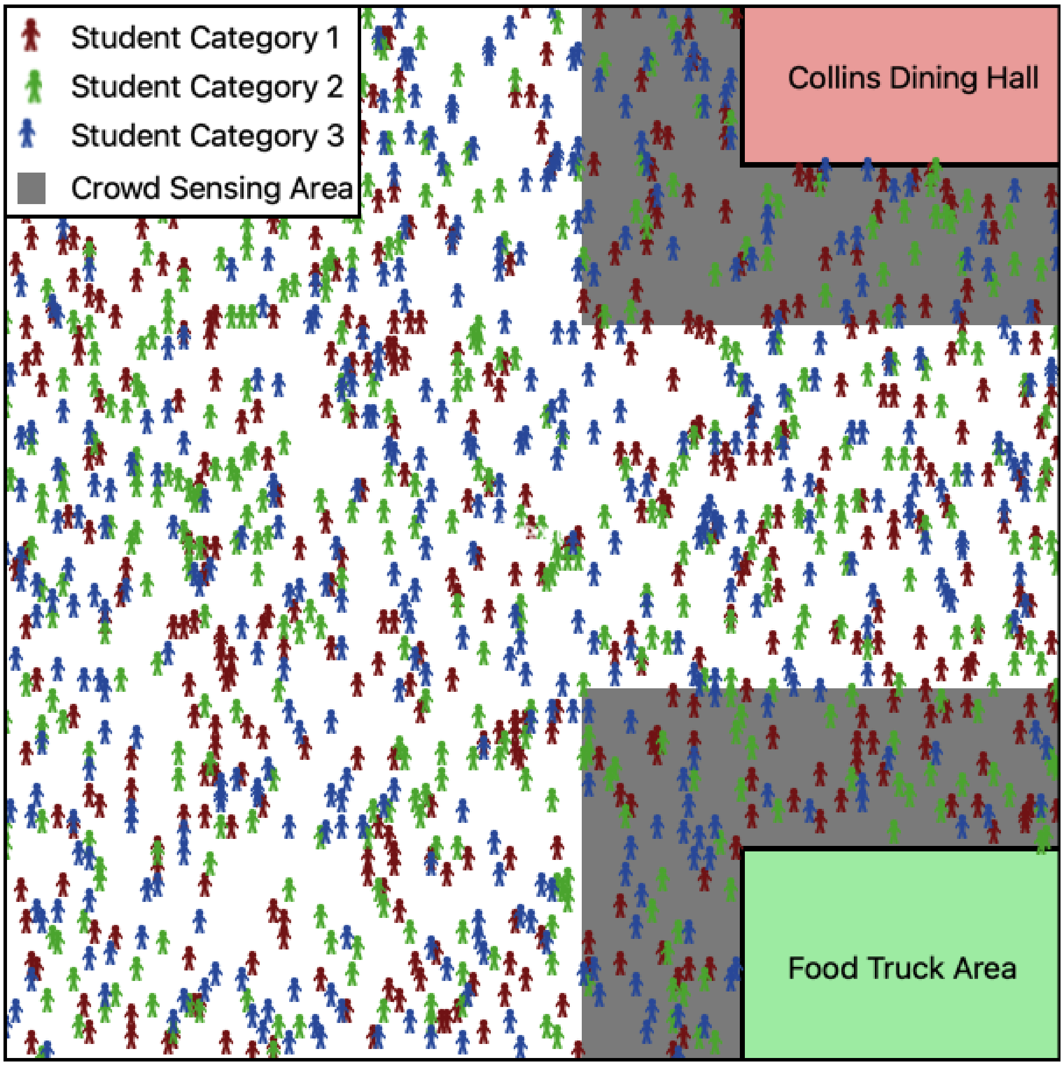



**Figure 3.** *Model setup for Version 3 which also doubles as the Base Model. In this model, a third student category is added (in blue) which has students whose initial dining preference can be changed (influenced) by other students upon interaction.*

The first extension to the Base Model involves adding a new food source as a control measure for overcrowding in the model. In this model, the new food source serves as an alternative option for students to go to. This new food source could represent a new food truck or any other possible alternative food sources that the school can think of. In this model, we create a fourth category of students who start out with this alternative food source as their preferred location. In doing this, we ensure that the total number of students in the model remains the same as in the previous models.

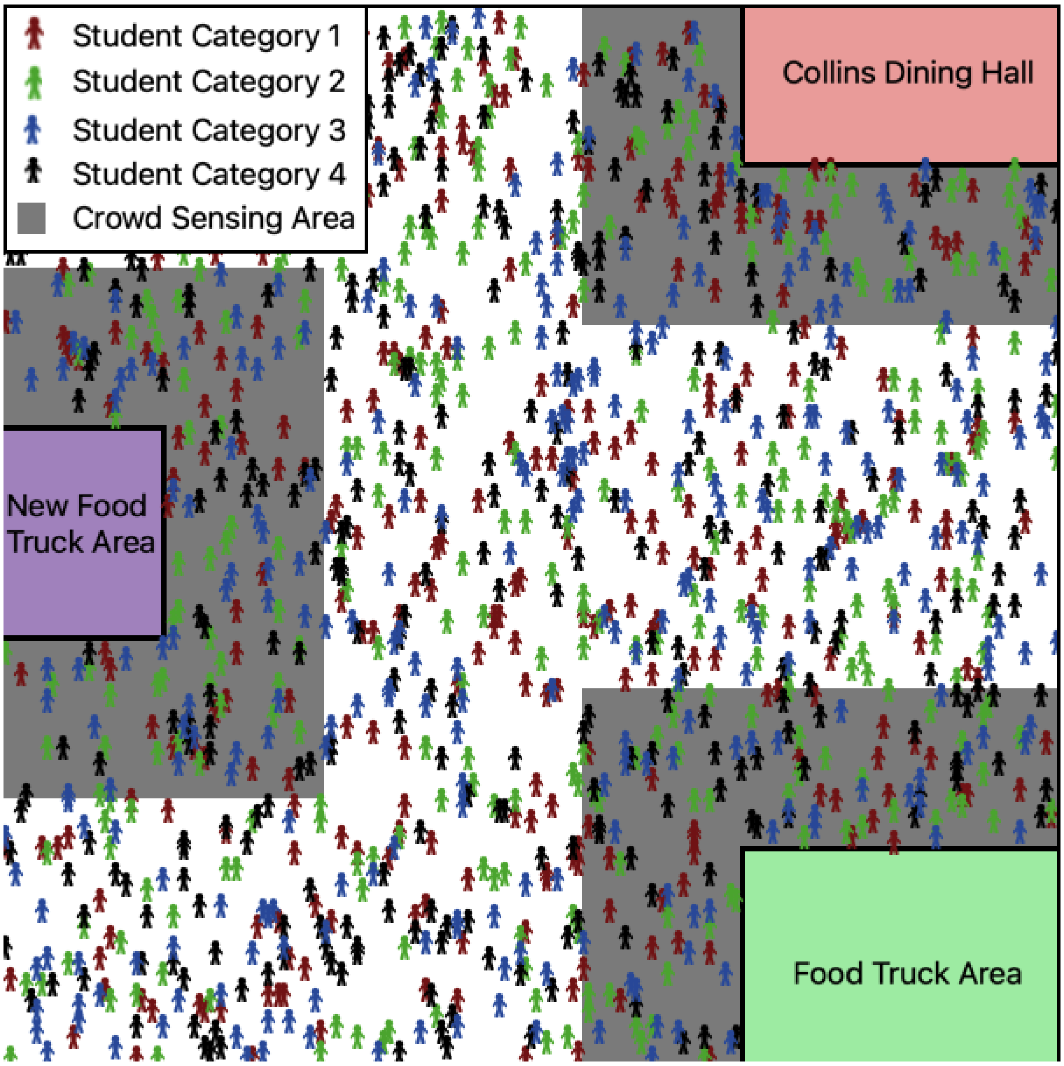



**Figure 4.** *Model setup for the Extension with a new food source. In this model, a new food truck area is added as well as a new student category (in black) whose default preference is to go to this new food truck area.*

The second extension to the Base Model comprises changing the the distribution of eating duration for all students in the model as a control measure to overcrowding. In this model, the distribution of eating duration for all students is changed so that we have a larger proportion of students who have a shorter duration of eating. This control measure mimics a situation where more people use the takeout service at the eating locations and hence do not need to spend as much time in the dining locations. It is important to note that this extension does not build on the previous extension, hence there are still only three groups of students and two food sources in the model as is true for the Base Model. More information on the purpose of the eating-duration variable can be found in Table 3.

**4. Analysis and Results.** The purpose of our analysis is to answer two fundamental questions: which behavior affects crowdedness the most and which control measure is most effective in reducing crowding?

In order to answer these questions, we created three kinds of graphs. We ran each version and control measure of the model ten times and recorded the attendance at Collins and the food trucks at every tick. We made a plot of boxplots for the attendance values for every five ticks because this allowed us to examine the variation between each of the ten trials. We chose to make the plot of boxplots cover the values from five ticks rather than just one to simplify the graph; each graph thus includes 40 boxplots spread over 200 ticks. The goals of these graphs was to compare the ways that each different version and control measure changed the amount of people in each dining hall.

The second type of graph we made was a line graph that showed the average attendance at Collins and the food trucks over the ten trials. We chose to make this graph in addition to the plot of boxplots because we wanted a clear way to compare attendance at Collins and the food trucks.

The final type of graph we made was a bar graph that recorded the duration of crowding in each dining hall for each type of model. The duration of crowding variable measures the total time that attendance at Collins or the food trucks was greater than the crowding threshold; in other words, how long crowding occurred. Each bar on the graph was the average of ten trials. These graphs were useful because they gave us a quantitative measure of how each version of the model or each control measure affected crowding.

**Which Behavior Affects Crowding the Most?**

Comparing the plot of boxplots of Versions 1, 2, and 3 of the model reveals that a strong preference for a dining option influences crowding the most.

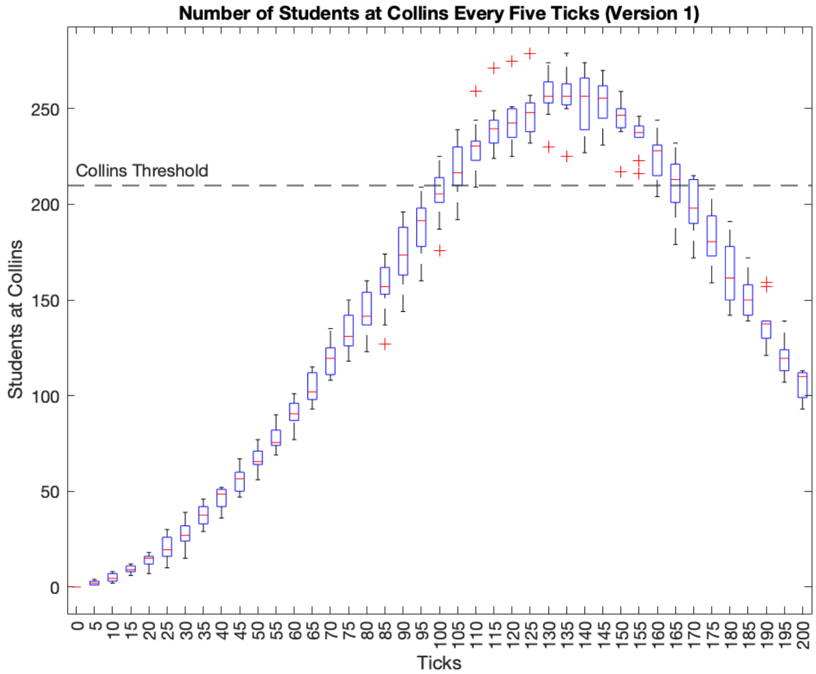



**Figure 5.** *Number of Students at Collins Every Five Ticks (Version 1). This graph comparing boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

Figure 5 shows the attendance at Collins under Version 1, in which there are only two groups of students–both of whom begin with a preference for Collins or for the food trucks. Nothing changes where the students go to eat. We find that the graph fits our expectations; the attendance distribution appears to be roughly normal: this is explained by the normal distribution of time-to-search-for-food that we gave to the turtles. Furthermore, although there is some variation between trials, as evidenced by the red x's that show outliers, most of the boxplots are quite compact, indicating that there are not substantial differences between each trial. We see the same trend in the graph comparing boxplots for the food trucks in Version 1 of our ABM.

The patterns we see in Version 2 also meet our expectations.

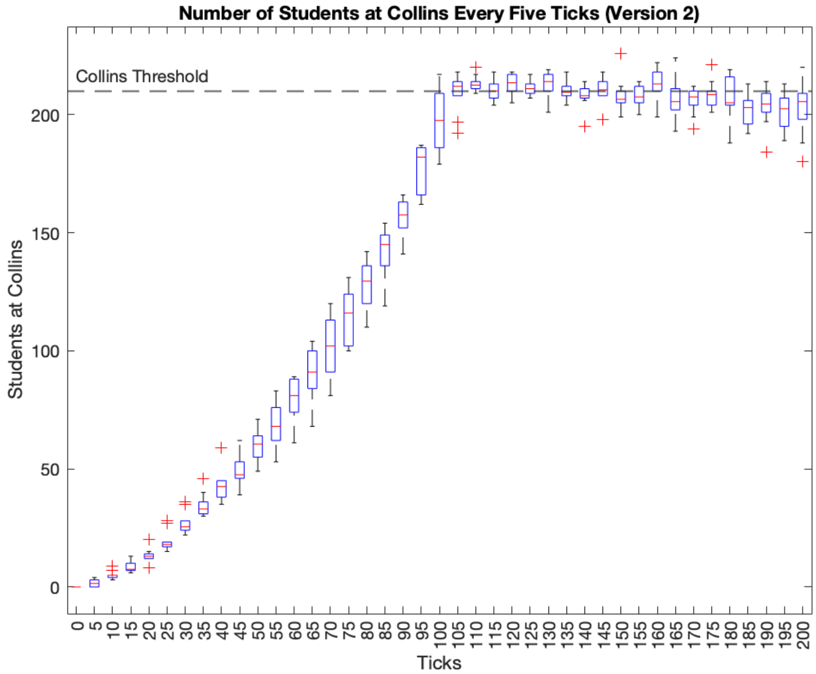



**Figure 6.** *Number of Students at Collins Every Five Ticks (Version 2). This plot of boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

In Version 2, we added the ability for both groups of students to sense crowdedness at the dining options. We see from Figure 6 that the number of students at Collins increases like in Version 1, until the number of students begins to approach Collin's crowding threshold. Here, the crowdedness sensing kicks in, and the attendance curve begins to fluctuate around the threshold. This is because some students will approach Collins, see that it is crowded, and then go to the food trucks.

We discovered from Figure 6 that the number of students remains much higher at the end of the simulation compared to Version 1. In Figure 5, because students were ignoring how crowded it might be, they were able to enter, eat, and then leave. At 200 ticks, only around 100 students remained in Collins. In Figure 6, slightly less than 210 students were left in the model. This signifies that high levels of crowding in Collins might be preventing students from having enough time to eat lunch before they have to go to another class or before the dining hall closes. This trend indicates that our model accurately mimics real-life, despite the fact that we did not explicitly program in our model how the effect of crowding (i.e., long wait times) could make it difficult for students to eat lunch in time. It is important to note that because some students were still waiting for Collins or the food trucks to be below the crowding threshold, a small group of students were still bouncing back and forth between the dining options at the end of the lunch period.

Version 3 of the model is where we saw a deviation from our expectations. This is shown in Figure 7.

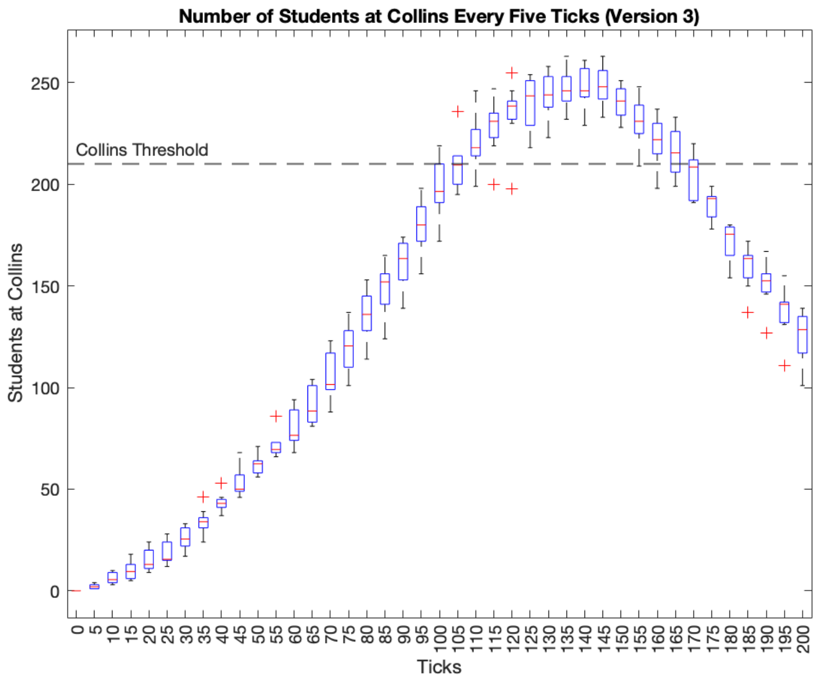



**Figure 7.** *Number of Students inside the Collins Dining Hall Every Five Ticks (Version 3). This graph comparing boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

In this version, we added a third group of people who could be influenced, meaning: if a person from a different dining option group came in contact with them, their dining preference could switch to preference of the person they came in contact with. However, this group is not able to sense crowdedness after they have been influenced. Given that the other two student groups and the students in the third group who do not get influenced keep their crowding sensitivity, we expected this graph to appear more like Figure 6, since at least 2/3 of students in the model can adjust their behavior based on whether or not the dining area has too many people. However, this graph resembles Figure 5 where no one can sense crowdedness, much more than Figure 6. This suggests that having a small subsection of students who stick to their preferred location has a significant effect on the overall level of crowdedness at the dining location, giving Figure 7, returning the distribution of the students to a normal distribution. And so, like with Version 1, the influenced turtles from the third group act only according to their time-to-search-for-food, which follows a normal distribution.

The fact that Version 3 resembles Version 1 indicates that the most important factor in whether or not Collins is crowded is whether a group of turtles have a pre-set preference that doesn't change based on crowdedness level. We find that the food trucks follow the same pattern as well for Version 3. In real life, this is represented by students who have a strong preference for one dining hall. This preference could be due to a number of things, such as lack of allergen-friendly foods at one dining area, accessibility issues, or simply personal taste.

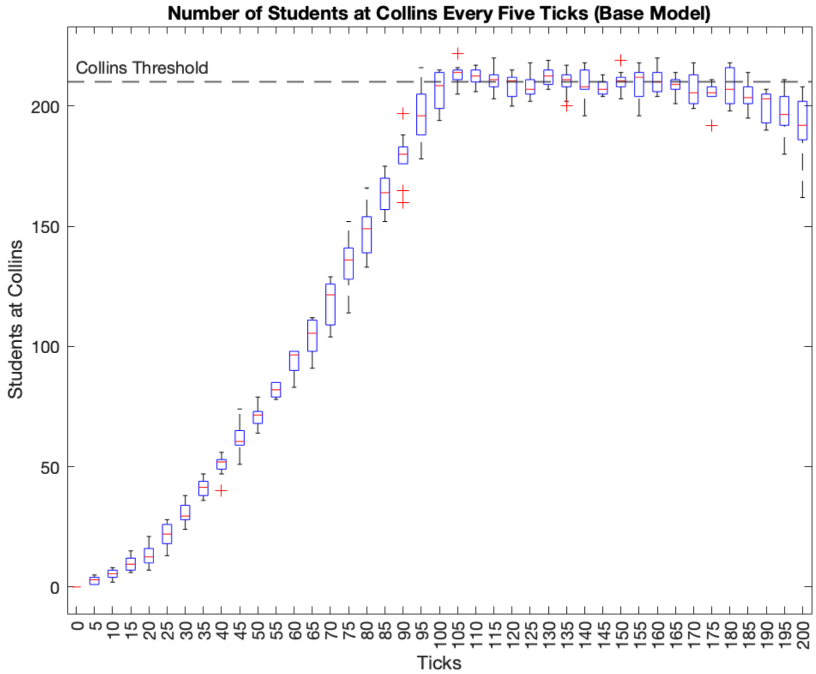



**Figure 8.** *Number of Students at Collins Every Five Ticks (Base Model). This plot of boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

Now we turn to our Base Model, the final version with all the factors we wanted to analyze. We find that this model behaved much like our Version 2 model. Figure 8 shows how the crowdedness level in the Base Model reaches the crowdedness threshold, then fluctuates around it and only decreases slightly towards the end. We did not find this behavior to be surprising since all three groups of students in the Base Model can sense crowdedness and from our analysis of Version 2, we know this fluctuation is an effect of the ability to sense crowdedness. Although the Base Model mirrors the results from Version 2, it is a crucial addition to our analysis because it added influence which is a more realistic representation of lunch time at CMC. Furthermore, the Base Model provides a standard enough base which we could modify to draw comparisons about different kinds of dining behaviors.

Comparing the graphs of Version 3 and Base Model provides further evidence that having a strong preference of where to eat is the most important factor in determining crowding. Version 3 and the Base Model both have three groups of students; the only difference is that the third group of students in Version 3 cannot sense crowdedness. We expected Version 3 to look more like the Base Model, since they share two groups of students who have a pre-set preference and can sense crowding. However, Figure 7 appears much more similar to Figure 5 (Version 1) than it does to Figure 8 (Base Model), indicating that having a small group of students who have a preference and cannot sense crowdedness is enough to completely change the shape of the graph. This suggests that having a strong preference of where to go is the most influential factor determining crowding.

However, due to time constraints, we were not able to further investigate the relationship between sensitivity and preference. One possible way of investigating this would be to create a model in which two groups of students have a strong preference for Collins or the food trucks and cannot sense crowdedness and the last group can sense crowdedness. This would allow us to examine the effect of crowdedness sensitivity in the same way we examined that of preference.

For the duration of crowding, we find that our hypotheses around the power of preference is supported by Figure 9 which shows the different duration of crowding in Collins and in the food trucks for model versions 1, 2, 3, and the Base Model.

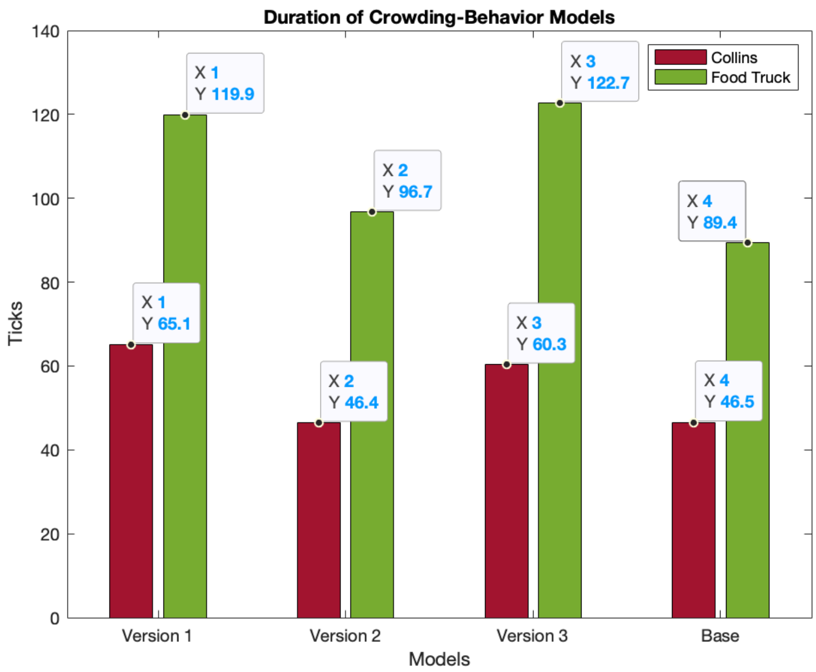



**Figure 9.** *Duration of Overcrowding (in ticks) inside the Collins Dining Hall and at the Food Truck Area for Model versions 1, 2, 3, and the Base Model. Values in this graph are averages from 10 simulations, each with a duration of 200 ticks.*

In Version 2 and in the Base Model, all groups of students can sense crowdedness. Because of this, Collins and the food trucks are crowded for less time than Versions 1 and 3. This trend was not unexpected since it could have been extrapolated from the box plots in Figures 5, 6, and 7.

It is important to note that the trends for the number of students at the food trucks are very similar to that of Collins and as such, we do not discuss those box plots in-depth here. See the Appendix B for the graphs.

However, we did compare the average attendance at the food trucks and Collins using the line graphs that show attendance averages from ten trials. The average graphs of Version 1 and 3, shown in Figure 10, behaved nearly identically as their box plots. Although both follow a similar normal distribution, we noticed a wider gap between the Collins and Food Trucks lines around the peak in Version 3. We can only speculate on the reason. Perhaps this is due to introducing the third group of people.

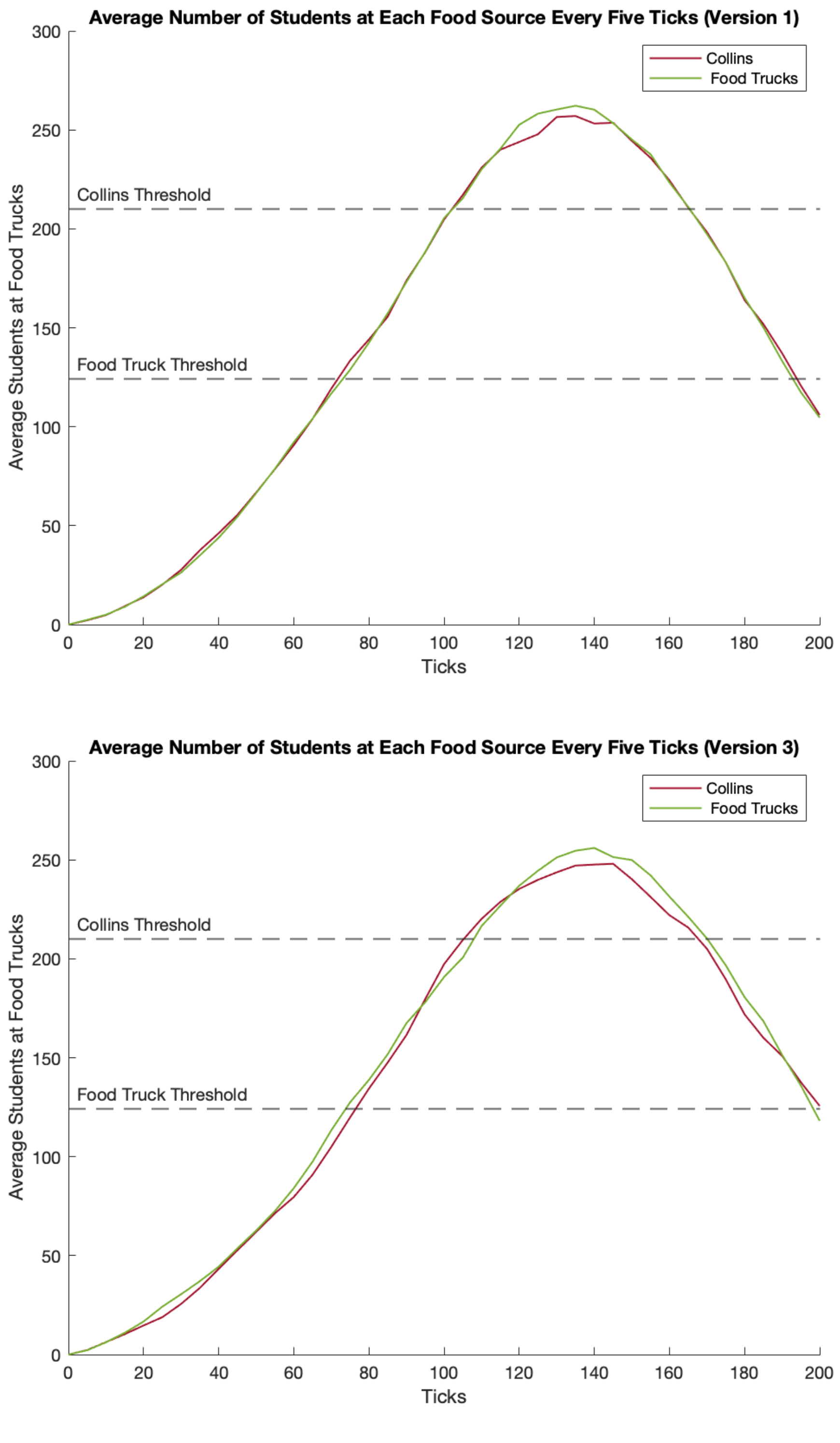
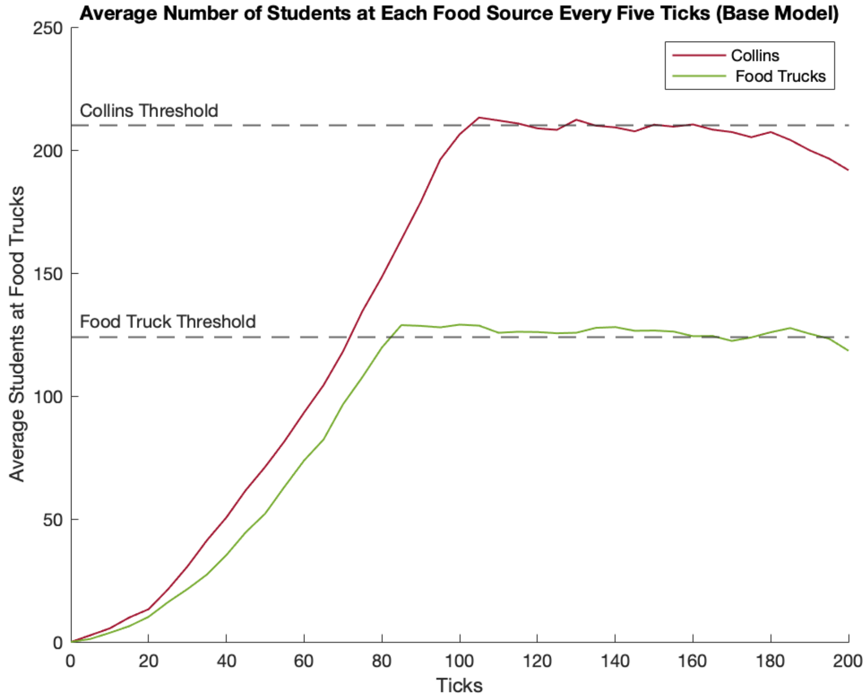



**Figure 10.** *The Average Number of Students at Each Food Source Every Five Ticks for Versions 1 (top) and 3 (bottom). These graphs were generated by averaging values from 10 simulations, each with a time limit of 200 ticks.*

However, the graphs of Version 2 and the Base Model revealed an interesting difference between the behavior of students at Collins and at the food trucks.



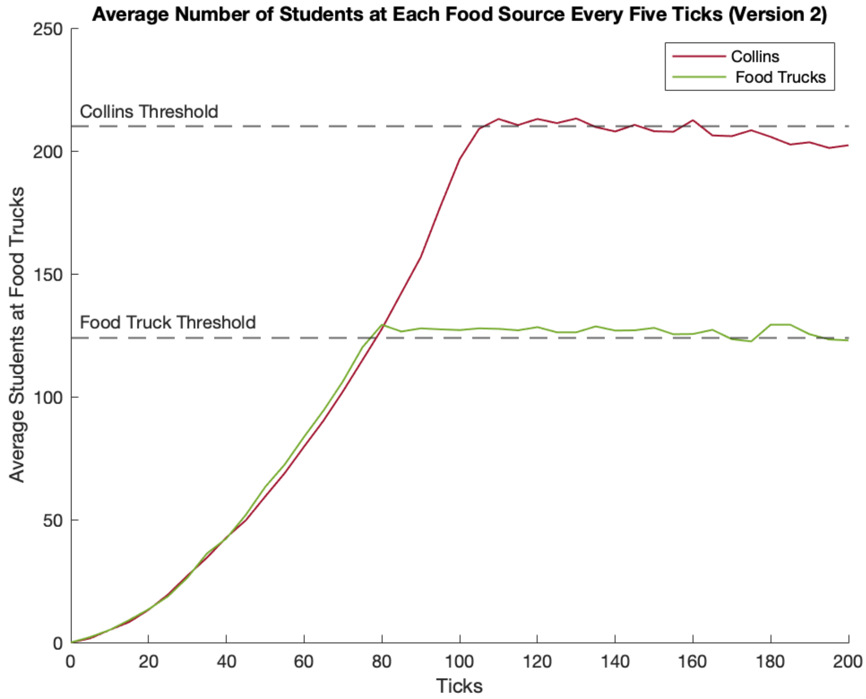




**Figure 11.** *The Average Number of Students at Each Food Source Every Five Ticks for Base Model (top) and Version 2 (bottom). These graphs were generated by averaging values from 10 simulations, each with a time limit of 200 ticks.*

Since both dining areas follow the same rules, we expected the attendance at both to vary equally around the crowding threshold. However, when examining the comparison of attendance at Collins and the food trucks under Version 2, we noticed that the food truck line and the Collins line behaved differently a round t heir r espective c rowding thresholds. We expected both lines to fluctuate s imilarly a round t he c rowding t hreshold o nce i t was reached; however, analysis of Figure 11 reveals that the food truck attendance stays above the crowdedness threshold for much longer than Collins attendance. Furthermore, once the food truck line grows larger than the threshold, it does not decrease below it until the last 30 or so ticks of the model. Since the students can sense crowding, this is odd behavior, since it means that some turtles are entering the food trucks despite it being crowded. How did this happen?

From our analysis, we constructed a possible answer. Based on how our exponential decay function works, most of the grey patches around the perimeter of each dining area do not contain perfect knowledge of the actual crowdedness value inside the dining areas (see environment section under Appendix A.2 for further explanation of the decay function). Moreover, at each tick, each student in our model individually senses the number of students in the dining area. An example illustrates why this is relevant. There could be 123 students in the food truck area, which is less than the crowding threshold of 124. If eight students are currently on patches that contain some crowdedness value that is 123 or less, they will all simultaneously decide to enter the food truck area to eat. This causes the number of students at the food trucks to increase to a level greater than the crowding threshold, which theoretically shouldn't happen since new students can't enter the areas once it is crowded. We see this effect a t b oth C ollins a nd t he f ood t ruck. A lthough i t e xplains w hy t he attendance lines sometimes go above the thresholds, it still does not account for the way that the number of students at the food trucks consistently exceeds the crowding threshold.

A possible explanation of why the number of food trucks consistently exceeds the crowding threshold emerges when we consider the fact that the food trucks have a lower threshold than Collins. Since it takes fewer people for the food trucks to become overcrowded, they become overcrowded sooner than Collins does. Now, recall that as the model progresses, people who have already eaten "die" and leave the environment. This means that at the time that the food trucks get overcrowded there are more students in the model than when Collins gets overcrowded. Since there are more students around the food trucks, there is a higher chance that there are people on patches surrounding the food trucks. These students have imperfect knowledge of how crowded the food trucks are and thus, will enter the food truck area to eat even after the crowding threshold has been reached. Comparing the graph of Version 1 and that of Version 3 in Figure 10 to the Base Model in Figure 11, we see that Collins becomes crowded relatively near to the peak of the normal distribution. This shows that Collins, unlike the food trucks, starts to get overcrowded at a point in time where the model starts to reach its natural turning point i.e., the rate of at which people go to their dining locations naturally starts to decrease. This is why the number of students at Collins does not consistently exceeds the crowding threshold like the way that the number of students at the food trucks does.

Applying this to real life, although this trend was unexpected, it mimics the dynamics at the food truck well. Fundamentally, it represents more people desiring to go to the food trucks than are able to; this is born out through qualitative observation of the food trucks, where there are often long lines due to the high desirability of the food. This supports our conclusion that having a strong preference for one location is the most influential indicator of crowding. Understanding the dynamics behind crowding in the dining halls is crucial as we move on to our second analytical goal: to propose ways to reduce crowding.

**How Effective Are the Control Measures in Reducing Crowding?**

Our analysis considered two different types of control measures: adding a third eating option, New Food, and changing the eating duration variable (how long a student will stay at the dining option for) to test how this would affect crowding (i.e., increasing the proportion of students who spend less time in the dining areas to examine its influence on crowdedness). The bar graph of the duration of eating in Figure 12 reveals that the most effective control measure was adding a new food source.

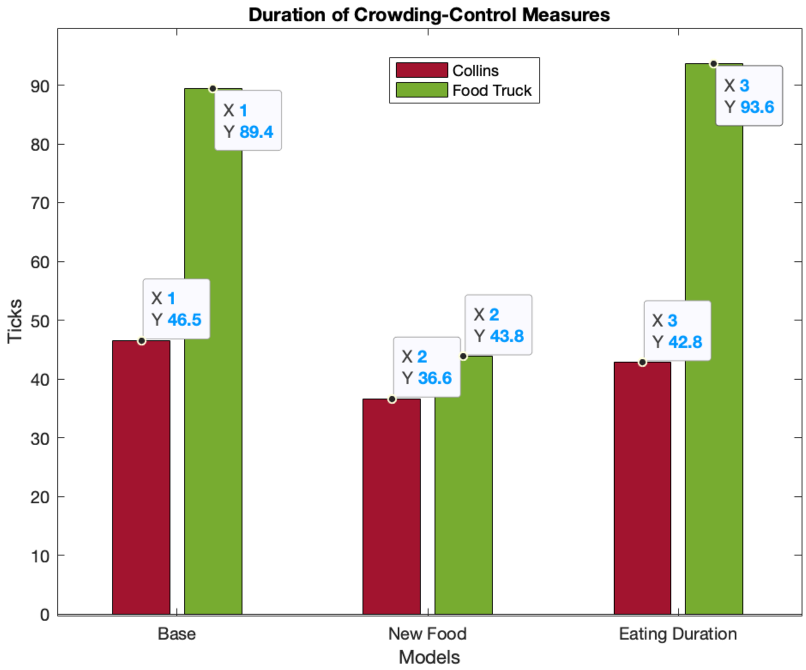



**Figure 12.** *Duration of Overcrowding (in ticks) inside the Collins Dining Hall and at the Food Truck Area for the Models with Crowding-Control Measures (i.e., the New Food control measure and Eating Duration control measure). Values in this graph are averages from 10 simulations, each with a duration of 200 ticks.*

Here, we see that the duration of crowding in both Collins and the food trucks is significantly less when a new food source is added than in the Base Model or when the eating duration is shifted. Although the Eating Duration Control Measure did reduce crowding at Collins slightly, the overall effect is negligible. We note that crowding is reduced much more at the food trucks than at Collins. The reason for this remains unclear, and warrants further research; however, it might be influenced by the fact that the food truck threshold is smaller, and so the food trucks feel the effect of having another food source more strongly. In other words, since the food trucks were crowded for longer, having an outlet for that crowd reduces their high duration of crowding.

Looking at a graph of the average number of students under the New Food control measure in Figure 13 adds more insight into why it reduces crowding.

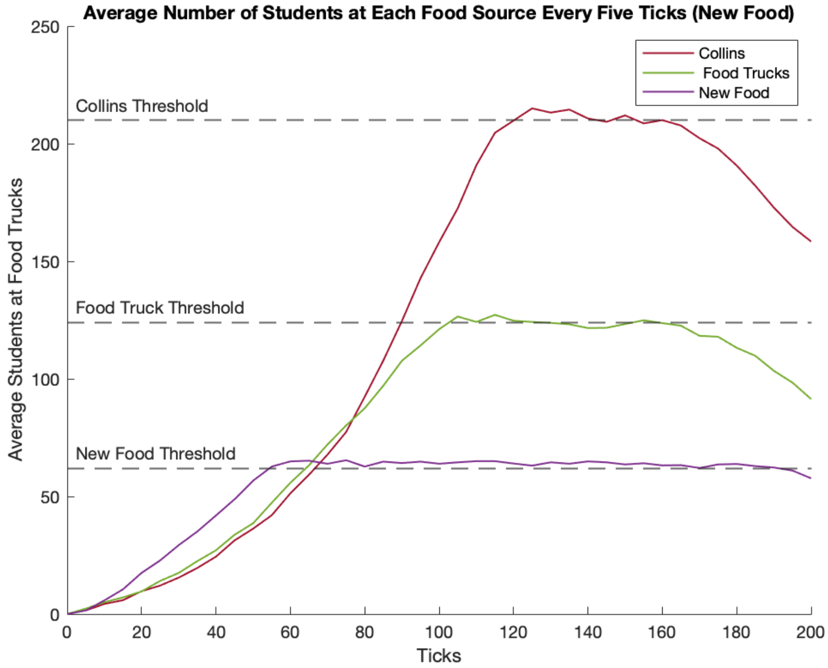



**Figure 13.** *Figure of the Average Number of Students With a New Food Source Added. These graphs were generated by averaging values from 10 simulations, each with a time limit of 200 ticks.*

Figure 13 demonstrates how the new food source behaves similarly to the food trucks in the Base Model. It becomes crowded quickly and stays crowded for most of the model. This allows the food truck attendance line and the Collins attendance line to begin to dip before the model is over, which is something that did not occur in the Base Model.

Taken together, these results shed light on the fact that it will be very difficult for CMC to reduce crowding in its dining halls by adding more grab-and-go options. It would be far more effective to add somewhere else for students to go.

**4.1. Sensitivity Analysis.** To formulate our parameters, we used the data available and made key assumptions. However, if some of these parameters are incorrect, they have the possibility of skewing our research findings, based on how sensitive our outputs are to these parameters. We conducted a sensitivity analysis on our threshold value for Collins and the ratio between the threshold value for Collins and the food trucks.

**4.1.1. Ratio Sensitivity.** Unlike at Collins, the food trucks themselves are not where the students line up; they crowd the area immediately surrounding the food trucks. This makes it difficult to accurately estimate how much of the space surrounding the food trucks should be considered to determine their threshold value. To get around this problem, we adapted the ratio between Collin's carrying capacity and the average number of students that go to Collins for lunch and applied that ratio to the food trucks, given the average number of students that go there for lunch [4]. We conducted a sensitivity analysis on this measure to investigate how it affects the accuracy of our research for the duration of crowding. We did this by varying the ratio between the food truck's threshold to Collins' threshold, holding everything else constant.

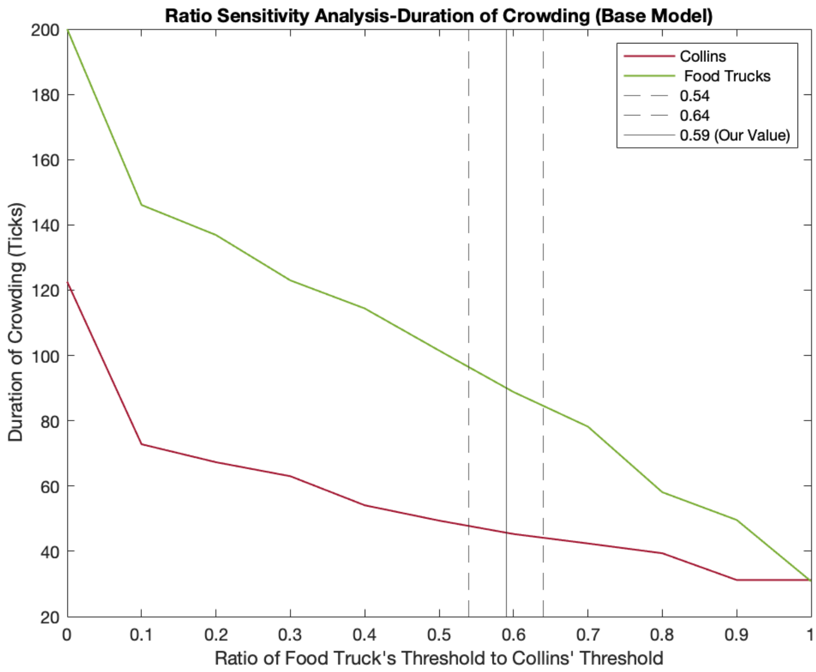



**Figure 14.** *Ratio Sensitivity Analysis - Crowding Duration (Base Model). Values in this graph are averages from 10 simulations, each with a duration of 200 ticks.*

Figure 14 illustrates the relationship between the average duration of crowding for each ratio value (over ten trials for each ratio for a total of 110 trials). As the food truck threshold's value gets closer to Collins' threshold value, we find that it decreases the duration of crowding. Although we are limited by the number of trials we conducted, the trend between the duration of crowding and the ratio mimics an exponential decay function. This indicates as the ration increases, it has a smaller marginal impact on the duration of crowding. This means that the duration of crowding is more sensitive to the ratio between the thresholds when the ratio is closer to 1.

In Figure 14, we highlight the area around the ratio we use in the Base Model, 0.59. This ratio is toward the latter half of the curve where the slopes are decreasing, showing a change in the ratio creates a smaller and smaller impact on the duration of crowding. Based on qualitative inferences on the number of COVID cases relative to the number of students that go to the food trucks for lunch, we can assume that the ratio of the food truck's threshold can be close to Collins threshold without causing a significant increase in COVID cases. And so, we maintain a reasonable amount of confidence in our ratio compared to the actual ratio having a minimal impact on our duration of crowding output.

**4.1.2. Threshold Sensitivity.** Another parameter that we estimated is the Collins threshold itself. This value was adapted from the El Farol's definition of crowding (60%) to our model; we made the threshold for Collins to be 60% of the space's carrying capacity to create this parameter. To test the affect of this value on the duration of crowding, we graph the relationship between threshold values ranging from 150 to 350. We do this to get a wide enough range below and above the threshold value that is realistic considering the space (i.e., we deduced that a value under 150 would not be a realistic threshold for Collins given the dimensions of the actual space). Running 10 trials for each value for a total of 110 trials, we varied Collins' threshold value, holding everything else constant, to investigate how it affects the average value of the duration of crowding.

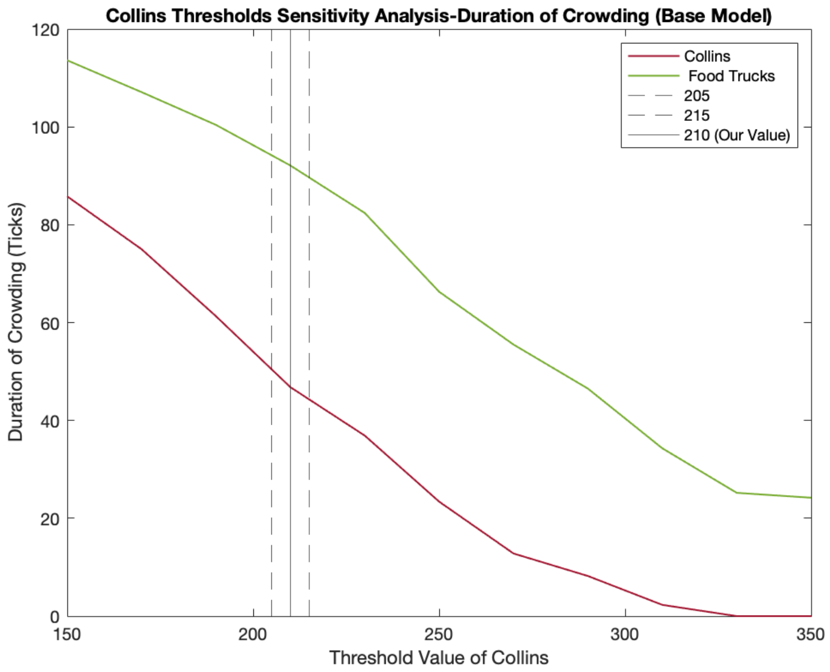



**Figure 15.** *Collins' Threshold Sensitivity Analysis - Crowding Duration (Base Model). Values in this graph are averages from 10 simulations, each with a duration of 200 ticks.*

Figure 15 reveals the relationship between Collins threshold value and the duration of crowding to be negative. Once again, our analysis is limited by the number of trials conducted, however, the data shows that the relationship between the Collins' threshold looks like a logistic decay function. From Figure 15, we found that our value, 210 students, locally does not have a large slope, indicating that a change in the threshold value, at least by plus or minus 5 students, does not have a substantial affect on the value of the duration of crowding. As with the threshold ratio between the food trucks' threshold and the Collins' threshold, the sensitivity of the duration of crowding on this parameter is greatly dependent on where the threshold value we use is in relation to where the actual value is. As long as the difference is not drastic (ex: a hundred people), the impact of this difference would be reasonably insignificant.

**5. Conclusion.** Our model creates a strong representation of real-life dynamics we observe of CMC's student body during lunch and provides novel insight by allowing us to examine how crowding changes over time. All versions of the model supported our qualitative observations that the food trucks seem always to be more crowded. Furthermore, although we did not explicitly program the effect of crowding into our model (i.e., that longer wait times would mean that fewer students had time to eat) we saw this occur in our Base Model with the large amount of students still left in the dining hall at the end of the model. These results reveal the strengths of our model which enabled us to realistically recreate the impacts of student choice and sensitivity to crowding in our model to observe the complex factors that influence students behaviors at lunchtime.

From observation of the Base Model, we noted a small but significant group of students who did not get to eat at all because they spent their time walking from the food trucks to Collins, searching for an open place to dine. Again, this accurately depicts real life, since intense crowding in the dining areas can lead to some students not being able to get food before Collins or the food trucks close. This result is significant for CMC, since it suggests that some students might be having to miss meals. This observation is supported by the real data from CMC Dining, in which we found that over the course of three weeks in November, only 560 students on average attended Collins, and 330 attended the food trucks during the lunch period [4]. Considering that the total population of CMC is around 1,400, this leaves hundreds of students unaccounted for. While there are likely many explanations for these statistics (such as eating out or cooking in a dorm), it is worth exploring further if some of these students are having to skip lunch because of crowding. In light of this possibility, our suggestions for crowd control become particularly important.

Given our findings, we suggest that CMC adds a new outdoor dining option. Our behavioral analysis revealed that having a strong preference for one dining hall was a major factor in crowding. CMC could mitigate this as much as possible without changing the actual menus of the dining areas by making sure that both are equally accessible. Moreover, our behavioral analysis revealed that having an ability to sense crowding decreased the duration of crowding at the food trucks and Collins (recall Figure 9). This indicates that CMC could reduce crowding by making it clearer to students how crowded it is in each dining hall. There is already a popular app that students use to find out the daily menu at the dining halls–CMC could add approximate wait times or the total number of students currently in the dining areas.

There are a few important limitations of our model. The fact that we created it to fill the gap left by a lack of time-based data means that we don't have input data with which to analyze the accuracy of our model. A way to make our model more accurate would be to collect this data, or spend time in the dining areas making qualitative and quantitative observations about the number of students. Another constraining factor in the accuracy of our model is the number of trials that we considered for our analysis. Ten trials is a relatively low amount; our analysis could be improved by increasing this number so as to ensure that individual variations between trials are not affecting the overall trend of the data.

Considering that one of the major motivations for our model was to analyze COVID-19 safety in the dining halls, our model is limited by the assumptions we made about how COVID-19 is spread. We assumed that crowding was the main factor that could increase the risk of COVID-19; however, observation in the dining halls reveals that many students eat close together, unmasked. This occurs whether or not the dining area is crowded, and is especially a concern in Collins, which is indoors. This also means that our choice of a crowding threshold at 60% of capacity is somewhat arbitrary, since COVID-19 could still be spread even if the level of students in the dining halls is under the threshold. To mitigate the risk of COVID-19, it becomes important for CMC to consider factors other than those expressed in this paper.

We suggest several future directions for this research. Since we suggest adding a new food area, it would be incredibly useful to perform a cost-benefit analysis of doing so. In terms of extensions to our model, a possible way to reduce crowding that we did not analyze is changing when students go to the dining halls. Recall that most students get out of class at 12:25, which causes a major rush at the dining areas. Modifying the time-to-search-for-food variable could test the effect of staggering class times to mitigate crowding. A future extension could also explore the effect of expanding hours of the dining areas. Another possible extension is to add a tiredness variable, since it is unlikely that students will have a fixed preference for one dining area. This tiredness variable could be a random possibility that some students switch preferences. Including this could allow us to extend the scope of the model; since it is likely that the probability of the student switching preferences would be dependent on the student's past history. In our current model, each run of the model is independent and represents a single day; we could extend the model to include multiple days in each run to more accurately simulate how students' decisions change over time.

**Appendix A. ODD Protocol.** The description of our model adheres to the ODD (Overview, Design concepts, Details) protocol developed to describe individual- and agent-based models [9].

**A.1. Purpose and Patterns.** In order to make the return to in-person learning safe, CMC needed to limit the close interactions between students as much as possible. Dining is one of the riskiest activities for contacting COVID-19 since a facial covering cannot be worn at all times and many students will be together inside. Thus, CMC had to modify their strategies for dining to limit the capacity of students inside the hall while making sure students are being fed. This led to the introduction of the food trucks; during the time that Collins is open for lunch, two food trucks are parked in between Crown Hall and Beckett Hall (residential halls). However, despite increases in places to dine, there is often crowding at the Collins and/or the food trucks due to long lines. Our model will replicate the lunch time dynamics in order to understand the movement of students during the lunch period to see where they congregate over the course of the period and if/when crowding occurs, where it happens and for how long. We will use this analysis to see which behaviors affect crowding and in what ways the college could reduce crowding.

Unfortunately, the dining data we were given by CMC only reports the total number of students who visited the dining areas. Since it is not time-based, it does not help us evaluate the accuracy of our model. However, we expect student attendance in each of the dining halls to follow a pattern based on how students theoretically behave at the dining halls. We expect that attendance in both will steadily increase as the model reaches peak lunchtime hours, around 12:30 pm. Once attendance at the food trucks reaches the crowding threshold, which is lower than that of Collins, we expect some of the students to switch their path to go to Collins, which will result in an attendance spike at Collins. As the model progresses, attendance at both should fluctuate around the crowding thresholds—this mimics the real-life flow of people in and out of the dining areas based on how crowded they are.

**A.2. Entities, State Variables, and Scales.**

1. **Entities:** The students are the turtles. There are three types of students (collectives): the students that are going to Collins no matter what, the students who are going to the food trucks no matter what, and the students who are going to the nearest dining option who change their course if they interact with other students. All of the types of students have the ability to sense crowdedness; however, only the third category of students is able to be influenced. If they run into a turtle with a pre-set preference, they change their destination to match that turtle's. This represents students who run into a friend and make a decision on where to eat based on where their friend is going.

   The Collins patches are the dining hall's square-footage. We exclude the outdoor seating because of its low effect on crowding the space around Collins. The food truck patches represent both of the actual food trucks as well as the area surrounding them to take into account the crowding that happens with the lines around the food trucks. The swipe station that is off to the sides is not included in the food truck space because of the quick turnaround from there to the food truck area and its distance away from the food trucks is far enough that crowding there doesn't contribute sufficiently to crowding at the food trucks.

To students' ability to sense crowdedness at Collins, we created the left side of Collins patches and bottom side of Collins patches where students can "see" if Collins looks crowded. In the same way, we created the left side of food truck patches and top side of food truck patches. This will be discussed in depth in the following section.

The grid for our ABM is (-100, 100) x (-100, 100) using a patch size three. We measured the distance on Google maps between Collins and the food trucks to be approx. 130 m, which is why we made the coordinates of the patches from -100 to 100 in both the x- and y- directions. In addition, Collins is approximately 60m by 30m in dimensions, so we represented it to scale in the interface. Each patch represents 1 m. One tick represents one minute in real time. The simulation will run for 200 ticks, which represents the three hours Collins and the food trucks are open for (11 am - 2 pm), plus an additional twenty minutes for students already in the dining hall to finish eating.

2. **Environment:** The environment of the model consists of two rectangles, one in the upper right corner of the world which represents the Collins dining hall and the other in the lower right corner of the world which represents two food trucks. The world is not wrapped which means turtles cannot wrap from one side of the world to the opposite side of the world. The Collins dining hall and the food trucks each have an area of patches surrounding them that contain values determining how crowded they are. Each patch in this area of patches has a crowdedness value that is calculated using a decay function based on the distance of the patch to the center of its respective location i.e., the Collins dining hall or the food trucks. As such, the further a patch is from the center of its respective location, the more inaccurate its crowdedness value is. This essentially mimics the real-world phenomenon of not knowing exactly how crowded an area is unless you get closer to it. The decay function is defined as follows:

$$c = a * (1 - b)^d \tag{A.1}$$

In equation (A.1), c represents the crowdedness value, a is the actual value of the number of people at the Collins dining hall or the food trucks, b is a constant that is chosen that determines how quickly the decay happens and d is the distance of the patch from the center of the Collins dining hall or the food trucks. For this model, we choose the decay constant, b, to be 0.005 as this value allows the decay function to realistically mimic a student's lack of perfect knowledge about crowdedness due to limited visibility.

This function is used to calculate the crowdedness value of every patch in the area of patches around the Collins dining hall and the food trucks which provide turtles with information on how crowded these locations are. In the Global Variables section, these patches are represented by the variable names left-side-of-collins-patches, bottom-side-of-collins-patches, left-side-of-food-truck-patches, and top-side-of-food-truck-patches.

3. **Global Variables:**

| **Global Variable Name** | **Role** |
|---|---|
| collins-patches | Collective name of patches that represent Collins dining hall. |
| food-truck-patches | Collective name of patches that represent the two food trucks. |
| campus-patches | Collective name of patches that represent the parts of campus that are not Collins or the food trucks. |
| max-people-collins | Records the historical maximum of people in Collins at one time. |
| max-people-food-truck | Records the historical max of people in the food truck area at one time. |
| left-side-of-collins-patches | Collective name of patches outside Collins on the left side from which crowdedness can be sensed by turtles. |
| bottom-side-of-collins-patches | Collective name of patches outside Collins on the bottom side from which crowdedness can be sensed by turtles. |
| left-side-of-food-truck-patches | Collective name of patches on the left side of food trucks from which crowdedness can be sensed by turtles. |
| top-side-of-food-truck-patches | Collective name of patches on the top side of the food trucks from which crowdedness can be sensed by turtles. |
| collins-attendance | Counts the number of turtles in Collins. Updates each tick. |
| food-truck-attendance | Counts the number of turtles in the food truck area. Updates each tick. |
| collins-crowd-threshold | The threshold above which Collins is considered crowded. This is set at 210 people (see initialization for explanation). |
| food-trucks-crowd-threshold | The threshold above which the food truck area is considered crowded. This is set at 124 people (see initialization for explanation). |
| collins-crowdedness-duration | Measures the total amount of time that Collins was crowded over the length of the model. |
| food-truck-crowdedness-duration | Measures the total amount of time that the food trucks were crowded over the length of the model. |

Table 2: Table of global variables and their roles

4. **State Variables:**

| **Turtle State Variable Name** | **Role** |
|---|---|
| time-to-search-for-food | Represents the time at which the turtle begins looking for food. Randomly assigned to each turtle from a normal distribution with a mean of 90 and a standard deviation of 45. This was chosen because we assumed that most students would attend lunch around 12:30 pm, after their 12:25 class gets out. Furthermore, time-to-search-for-food cannot be less than 0 or greater than 180, since these are the hours of Collins. |
| in-eating-area | Represents how long the turtle stays in the eating area that it has chosen. |
| location-preference | For the two groups of turtles with a set location preference. This is initialized as either a preference for collins-patches or food-truck-patches. |
| i-was-influenced | For the third category of turtles who have no set location preference but have the ability to be influenced. Tracks whether or not they ran into another turtle with a location preference who influenced their choice of dining. The purpose of this true/false variable is to see how many turtles were influenced. |
| wiggle-angle | The random angle at which turtles turn as they move around campus-patches before they begin searching for food. |
| time-start-eating | Represents the time at which turtles "begin eating," i.e., make it to their dining option. Important for making sure that they only stay there a specific length of time. The turtles "die" (vanish) when the tick count is greater than the time that they started eating plus their assigned eating-duration time. |

| | |
|---|---|
| eating-duration | Represents how long turtles stay in the dining area. Randomly assigned to each turtle from a normal distribution with a mean of 45 and a standard deviation of 20. This was chosen because we assumed that people stay in the dining halls for an average of 45 minutes. In addition, we assumed that people wouldn't spend less than 15 minutes (approximate time it takes to get food) or greater than 90 minutes, so eating-duration is bounded between those two values. |

Table 3: Table of Turtle State Variable and their Roles

| **Patch State Variable Name** | **Role** |
|---|---|
| collins-crowdedness | Shows how crowded Collins is. Only gray patches (patches surrounding the dining areas) have this variable. Patches that are closer have a crowdedness value closer to the actual number of turtles in the dining area. As patch distance from the center of the dining area increases, accuracy of crowdedness value decreases. This represents people being able to more accurately judge how crowded a dining area is the closer they are. |
| food-truck-crowdedness | Shows how crowded the food trucks are. Follows the same law of decreasing accuracy as the gray patches around Collins. |
| distance-from-location | The distance of each gray patch from the center of Collins (for the patches around Collins), or from the center of the food truck area (for the patches around the food trucks). |

Table 4: Table of Patch State Variables and their Roles

**A.3. Process Overview and Scheduling.** Below is the schedule for our ABM's simulation:

**Schedule: Code Actions**

1. The environment executes the "setup" procedure which includes:
   (a) The environment creates food-truck-patches, collins-patches, and campus-patches.
   (b) The environment creates 3 categories of students of equal numbers using the "create-category-of-students" submodel.
   (c) The environment then creates the crowdedness range using the "create-crowdedness-range" submodel.

   (d) The environment sets values for the "collins-crowd-threshold" and "food-trucks-crowd-threshold" global variables.
2. The patches execute the "calculate-crowdedness" submodel and update the global variables max-people-collins and max-people-food-truck.
3. The "meet" submodel is called to allow turtles to influence or be influenced by one another.
4. The turtles move randomly using the "random-movement" submodel until the ticks exceed their assigned time-to-search-for-food.
5. When the ticks exceed their assigned time-to-search-for-food, they execute the "search-for-food" submodel, which includes the following:
   (a) Updates the location-preference based on whether their preferred location is crowded or not.
   (b) Advances the turtle by 5 steps after making it face its preferred eating location.
   (c) Updates the in-eating-area turtle state variable when the turtle gets to their eating area, sets the time-start-eating-variable, and calls the "eat" submodel.
      i. The "eat" submodel makes the turtles move randomly within the eating location of their choice until the number of ticks exceeds their eating-duration + the time they started eating. After this point, they leave the model using the die primitive.
6. The environment adds a tick to the clock. If the number of ticks exceeds 200, the model ends.

**Schedule Qualitative Description**

1. Turtles (the students) start in different locations.
2. When it's the student's time to eat (determined by the variable, time-to-eat) the student heads toward their preferred location. This preferred location is either pre-set to be Collins (red students) or the food truck (green students), or is the nearest option to where the student begins in the model (blue students in Version 3 and beyond).
3. If a student has the ability to be influenced, the student may change direction based on whether or not they run into a student with a pre-set preference.
4. As the student gets closer and closer to their preferred location, they can gradually get a better and better picture of if that dining option is crowded or not.
5. If the students perceive their preferred dining option is crowded, they will switch to their other dining option.
6. Once the student has arrived at a dining option, they stay there (determined by their duration-of-eating variable).
7. The patches are continuously updating the number of students that are at each dining location using a decay function that increases the next student's ability to predict how busy a dining option is as they get closer to the dining option.
8. Once the student is done eating (determined by their eating-duration variable), they leave the system.

### A.4. Design Concepts.

1. **Basic Principles**
   CMC students take into account the following elements when deciding where to eat:

(a) Which dining option has food options I prefer (or what are people saying is a good option right now)?
(b) How long would it take me to get my food?

There are many other factors that contribute to a student decision, but by observation of the CMC student body, we found these questions to be the most important; however, each student ranks these questions differently. To address these different perspectives: we take into account food preferences by having three different groups: a group that prefers Collins food, a group that prefers the food truck food, and a group that bases their preference on what they hear other people say. As for the second question, this is based on crowdedness: although this is a COVID safety issue, it's also an inconvenience for students trying to get their food before class. Allowing the turtles to predict crowdedness as they get closer to their dining option adds this student concern to our model.

Furthermore, CMC courses are designed so that there are no courses that completely overlap with the lunch hours. Most of the students get out of class around 12:30 pm which dramatically increases the influx of students to the dining halls until the next available class period (1:20 pm). This tight turnaround decreases the number of students that eat at Collins for the lunch period, but because of the boxing-out option, it does not decrease the number of students that are in the dining hall to get food, increasing the crowding from long line formation. However, in terms of acceptable lunch options, most CMC students have enough food preference overlap and so students will influence each other's decisions based on if someone says one option that day at the food trucks is great or if someone says one option at Collins isn't good.

The strength of habit formation and convenience play contrasting roles in the dining hall experience. Due to habit, students may create a loyalty to one dining option because it has become a habit to go there. And with most students at CMC having congested schedules, dining habits will stick by convention. However, students may also choose whichever option is the most convenient for them to save time (by how far it is and/or how long it would take for them to get their food). These students would be the most affected by crowding since they do not have a strong preference for the food they are being served.

There is also a preference for interaction at CMC as well: even if people are not eating together, if someone they know is going to Collins, it increases their likelihood of going to Collins as well to talk with them as they go there (the same is true of the food trucks). Thus, our model needs to simulate the natural crowding pattern of the dining halls.

2. **Emergence**

   The model provides data on where the students end up, how long it takes for a student to arrive at their dining option, the types that the dining options are crowded/for how long, and which students end up at each dining option.

3. **Adaptation, Learning, Objectives, Prediction**

   Based on the decay function on the patches used to give the students a sense of the congestion of their chosen dining option, the students are learning with an increasing amount of accuracy as they get closer to the dining areas how many people are eating lunch there. This ability to adapt their decision based on crowdedness information that updates with every tick determines if they will continue in that direction or if they will head toward the other dining option.

4. **Sensing**
   The patches know how many students are at Collins and/or the food trucks based on their location in the world. The accuracy in how many students are at either location is based on a decay function described in Appendix A.2 under environment. The students know their location, where the Collins patches and the food truck patches are, whether or not they have been influenced by another student, their time to head to a dining hall, and how long they will "eat" in the dining hall. If they are within 30 m of either dining area, they also know how many people are currently in the dining area with an increasing degree of accuracy as they get closer. This value is contained in the food-truck-attendance and collins-attendance global variables.
5. **Interaction**
   In our model, students interact with each other when their representative turtles touch one another. The effect of interaction is that some students can be influenced by other students when they touch. More specifically, turtles in the category of turtles who can be influenced change their eating location preference and color to that of one other turtle they interact with. This interaction is implemented by the "meet" submodel in Appendix A.7. This simulates how students' dining preferences get influenced by friends on their way to lunch.
6. **Stochasticity**
   The starting locations of each student is determined randomly to avoid bias in where the students start since they can realistically come from any direction on the map.
7. **Collectives**
   There are three defined collectives for the students: the students that prefer Collins, the students that prefer the food trucks, and the students that prefer the dining option that is the closest. The third collective changes based on interaction with the first two.
8. **Observation**
   In this model, we collect how often Collins or the food truck areas are crowded and at what times. We also collect how long each location is crowded for.

**A.5. Initialization.** The world begins by randomly placing the students across the map on any empty campus patch. For the simulation, no students start at any of the dining options. The beginning time is 11 am at tick = 0. There are 1,329 total students, split evenly into three groups of 443: those who initially head to Collins, to the food trucks, or to the dining option that is closest to them. This number was chosen because the number of students that attend CMC for the 2021-2022 school year is 1,414 [1]. According to CMC's website, 94% of CMC students live on campus, which is around 1,329 students [3] . We only included these students in the model because we hypothesized that on any given day, these students were most likely to be the ones going to lunch on campus.

We set the Collins crowding threshold at 210 because Collins' capacity, according to our in-person investigations, is 350 people. Sixty percent of this number is 210, which was chosen as it is the standard in previous ABMs like the El Farol Model and the Minority Game Model [6] [7].

Choosing the food truck's crowding threshold was more difficult. To do this, we used the data that CMC Dining gave us [4]. This data was in the form of a spreadsheet that included the amount of students who attended breakfast, lunch, and dinner at Collins, the food trucks, and various other CMC eating areas (such as a student cafe) from Nov. 1, 2021 to Dec. 1, 2021.

We averaged the lunchtime attendance at Collins and the food trucks over the month of November, excluding data from Thanksgiving week, when many students return home to celebrate. We found that, on average, 560 students attended Collins over the course of the lunch period, while 330 students got lunch from the food trucks. We divided the capacity of Collins, 350, by 560 to determine the ratio of the capacity of Collins to the total attendance. We used this number, 0.625, and multiplied it by 330 to determine the approximate capacity of the food trucks: 206. Then we multiplied this number by 0.6, just as we did with Collins, to end up with our final crowding threshold number of 124.

**A.6. Input Data.** Input data that was used in our model was Bon Appetit Data about Collins dining during lunch hours. As mentioned above, this data was a spreadsheet with student attendance during breakfast, lunch, and dinner hours at Collins, the food trucks, and other food areas that we excluded for the purposes of this project [4]. We also used dimensions of the Collins dining hall which we got from Google Maps (the dimensions and the estimated distance between Collins and the food trucks), and the information about the number of students at Claremont McKenna College which we got from the website [1].

In addition, one of our researchers is a CMC student. Their personal exposure to these dynamics has allowed us to make qualitative assumptions to guide the choices we make in our model.

**A.7. Submodels.**

1. **Create-category-of-students [category-color location]**
   This submodel allows us to easily create our four different categories of students, through a for loop, so that we can diversify our representation of dining preferences and how they influence one another. We pass in category-color and location as arguments to specify what color the category of students being created should have and what their preferred eating location is.
2. **Random-movement**
   This submodel structures the movement of students before it is their time-to-eat so that we can model how the student body go to the dining halls at different hours of the lunch period, but they can also be in that area before it is their time to go.
3. **Search-for-food [destination-patches]**
   This process structures the students' movement to search for the dining option they are going to. It stops their search once they find the dining option (to simulate staying at the dining option to eat/or waiting in the lines to get the food). They move randomly within the eating location once they have found it. The dining option being searched for is specified by the "destination-patches" argument.
4. **Move-to-empty-one-of [location]**

This submodel is called on turtles to make them move to an empty patch in a collection of patches specified by the argument “location.” For instance, move-to-empty-one-of collins-patches would move a turtle to one of the collins-patches which is empty. We use this to simulate more realistically how students would be arranged in the space.

5. **Create-crowdedness-range**
This submodel creates patches around Collins and the food trucks from which agents can receive information on how crowded the locations are. These patches are essentially grouped to form rectangles that surround the eating location. For instance, the crowdedness-range for the Collins dining hall patches consists of a rectangle of gray patches on the left side of the Collins patches and a rectangle of gray patches on the bottom side of the Collins patches. Once the grey patches are created, a distance-from-location variable is set for each of them. This variable represents how far the gray patch is from the location it is surrounding. It is calculated using the Netlogo distance primitive [11]. An example of how we use this primitive is as follows: ask-concurrent crowdedness-range-patches [ set distance-from-location ((round distance patch x y) - $\beta$)] where x and y are the coordinates of the center patch of the location, and $\beta$ is a constant that we subtract from the distance to the center of the location in order to mimic calculating the distance of the patches to the walls of the location and not the center of it. $\beta$ is calculated by $\frac{(l+w)}{2}$ where $l$ is the perpendicular distance between the center patch and the bottom boundary of the location and $w$ is the perpendicular distance between the center patch and the side boundary of the location. $\beta$ is essential to ensure that the decay function described in the environment section in Appendix A.2 represents incomplete information of crowdedness in a realistic way. i.e., the values of crowdedness in the patches closest to the boundaries of the eating location are not reduced too drastically.
6. **Calculate-crowdedness**
The ”calculate-crowdedness” submodel updates the crowdedness values of the patches in the crowdedness-range that was previously described. The crowdedness values are calculated in such a way as to simulate the patches having incomplete knowledge of how crowded the locations are. For instance, patches in the crowdedness range around Collins that are further away from the Collins patches will have a smaller record of the number of people at Collins than the actual number of people at Collins. This behaviour is achieved because this submodel calculates crowdedness using a decay function which is described in the environment section in Appendix A.2.
7. **Meet**
The ”meet” submodel simulates how a turtle interacts with other turtles and has its dining preference influenced by another turtle. In our model, turtles that can be influenced are colored blue. Therefore, this submodel is able to detect that a turtle can be influenced by checking its color. If the turtle can be influenced, it picks a random turtle out of the number of turtles that may be around it. If the random turtle picked is not a turtle that can be influenced, the initial turtle adopts its color and its location preference. Then the initial sets an “i-was-influenced” variable, shown in Table 3 to true. Thus, the turtle that was influenced will pursue a different dining preference. Note: turtles that can be influenced are only influenced once and only by other turtles

to the right of them. The decision to have them only influenced by other turtles to their right was an arbitrary decision and can be changed to have them be influenced from any or all directions. This decision was made partly because it was simpler to code and also because it introduced a probability that blue turtles are not influenced when they interact with other turtles. More precisely, blue turtles have an average probability of 0.25 (1/4) of being influenced every time they interact with other turtles from all directions. The code for how the turtles interact in this model was inspired by the "GenDrift T interact model" from the Netlogo library [2].

8. **Eat [name-of-patches]**
The "eat" submodel is called for turtles. It takes in the name of a collection of patches, represented by "name-of-patches" and checks to see if the turtle's allotted time for eating has passed. i.e., if the number of ticks is greater than this time-start-eating + eating-duration. If so, the turtle is taken out of the model using the die primitive [11]. Otherwise, the "move-to-empty-one-of" submodel, described in Appendix A.7, is used to make the turtle move around in its eating area until their time for eating passes.

## Appendix B. Graphs and Figures.

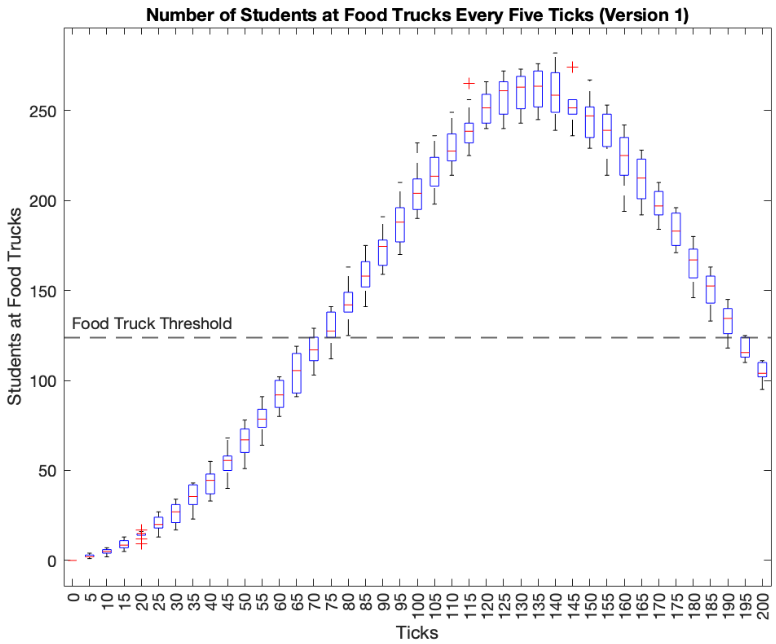



**Figure 16.** *Number of Students at Food Trucks Every Five Ticks (Version 1). This plot comparing boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

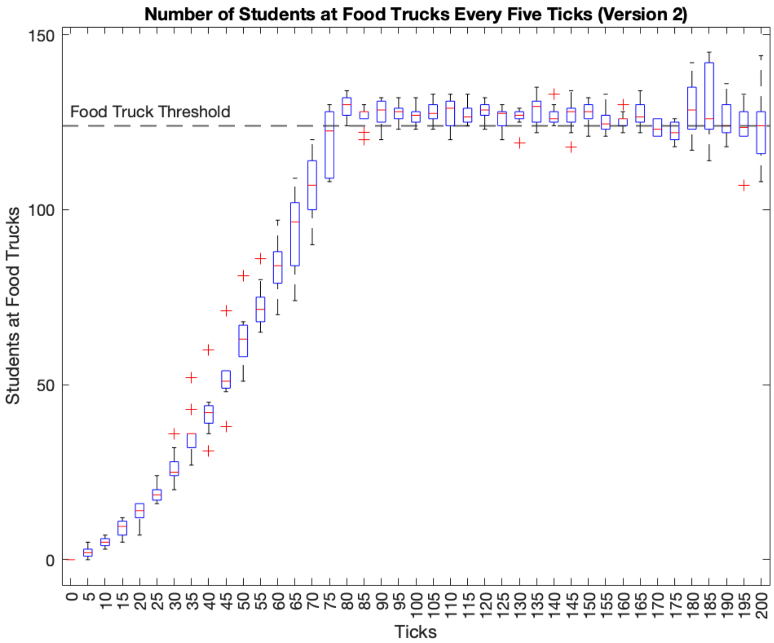



**Figure 17.** *Number of Students at Food Trucks Every Five Ticks (Version 2). This plot of boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

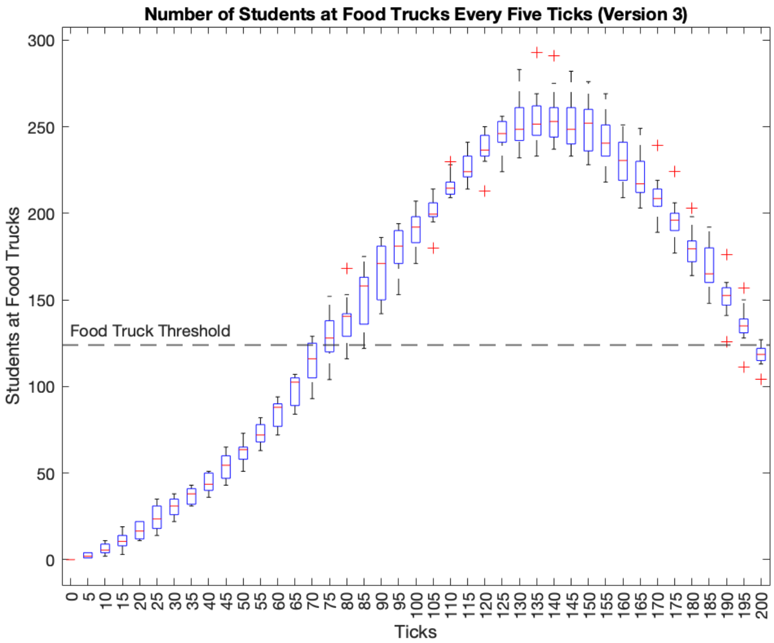



**Figure 18.** *Number of Students at Food Trucks Every Five Ticks (Version 3). This graph comparing boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

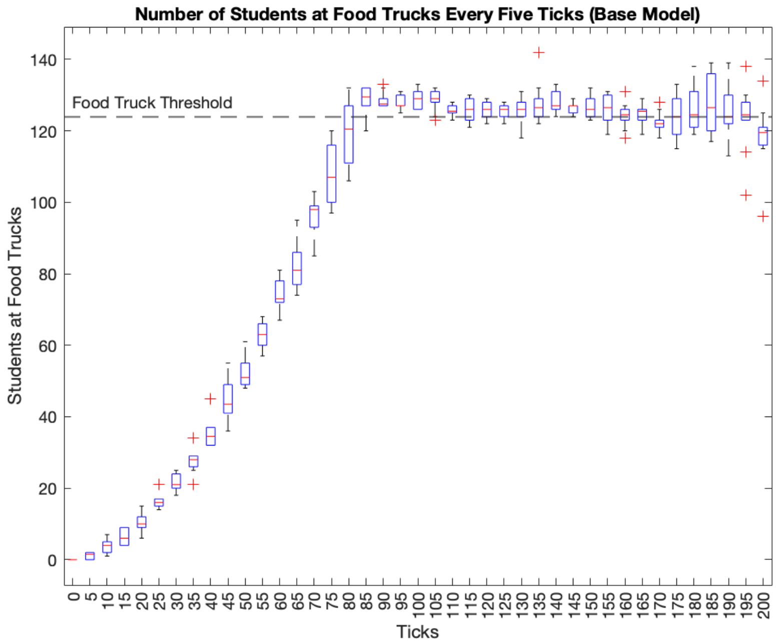



**Figure 19.** *Number of Students at Food Trucks Every Five Ticks (Base Model). This plot of boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

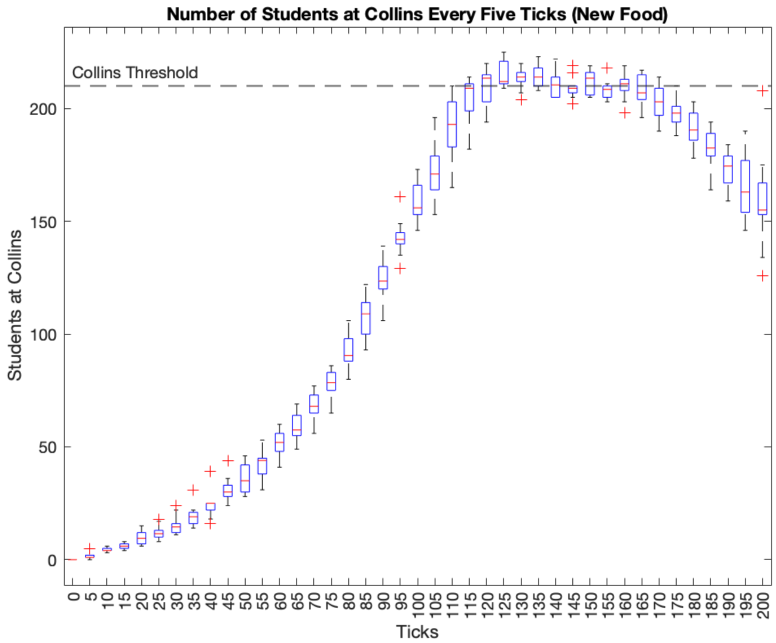



**Figure 20.** *Number of Students at Food Trucks Every Five Ticks (Exension with New Food Source). This graph comparing boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

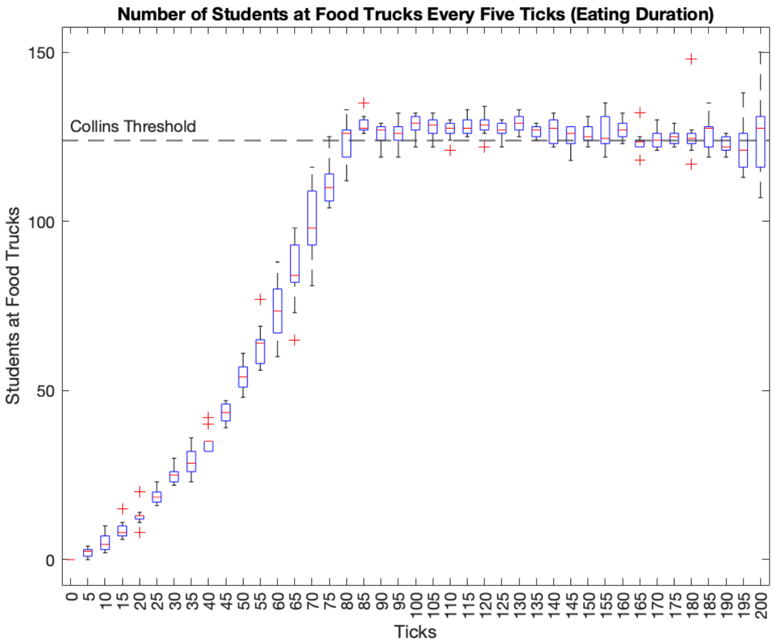



**Figure 21.** *Number of Students at Food Trucks Every Five Ticks (Extension with Different Eating Durations). This plot of boxplots was generated by running 10 simulations, each with a time limit of 200 ticks.*

**Appendix C. Netlogo Code.** Visit the GitHub repository to view the code at https://github.com/Omarzintan/cmc-dining-repo

**Appendix D. Matlab Code.** Visit the GitHub repository to view the code at https://github.com/Omarzintan/cmc-dining-repo

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