Design of a University Pandemic Response Decision Support System

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Abstract: The global effort to combat the COVID-19 pandemic has changed how people conduct their daily lives. Institutions of higher education have been greatly impacted by these changes and must find ways to adapt to this new environment. Universities are a unique case because they must control disease spread, while maintaining the same or similar quality of education. The University Pandemic Response Decision Support System (UPRDSS) is a system designed to help universities pick the most suitable method for instruction delivery when faced with any pandemic. Using George Mason University as a case study, the goal was to design a system that allows university administrations to make an educated operations decision. The UPRDSS achieves this by simulating the spread of disease, analyzing learning outcome data, and using a multi-attribute utility function to determine the most appropriate method of instruction that enables positive learning and health outcomes.

Keywords: COVID-19, Decision Support System, University, Infectious Disease, Pandemic

1. Introduction

The novel coronavirus, scientifically known as SARS-Cov-2 or COVID-19, is a rapidly spreading airborne illness that has affected millions of people throughout the world. Infection and death numbers continue to steadily rise. The novel coronavirus has a global mortality rate of about 3%; which makes it about 32 times deadlier than the average yearly seasonal flu. With numbers that high there are many limitations that have forced much of the world to switch to lockdown, public restrictions, and preventative measures. Abrupt and sudden changes in the daily routines of many people's lives have caused universities to change their operational protocols, with most switching to online learning platforms. This has caused a lack of participation, less interest in performing class assignments, and an overall decline in GPA (Jacobsen and Forste, 2011) (Carver and Muhkerjee, 2017). According to our source at the George Mason Provost Office, these are due to the fact that many instructors were not prepared for such a rapid and abrupt switch to online learning, with many not having adequate training and established measurements for courses. George Mason University (GMU) implemented a quick plan without much regard to maintaining the integrity of the learning capabilities that make a university a university. Towards the end of the semester, a plan for allowing students to select a pass/fail option was presented as a reaction to the reduced learning effectiveness caused by the immediate prioritization of reducing the viral spread. In a 2015 TED Talk, Bill Gates said that the world is not ready for the next pandemic and that in the coming years it will be more likely that an infectious virus would kill 10 million people than a war. Colleges and universities, like GMU, will need a quick and effective system to make an educated operations decision, with inputs of historical information from this pandemic and relevant viral data provided by the CDC or the WHO(World Health Organization). As hubs of learning and socialization, universities are unique within this context as they house and host students from all over the region, state, and the world. If universities do not have established, tested, systems in place, they can quickly become hotspots for diseases like COVID-19 and other airborne and aerosolized illnesses.

The spread of COVID-19 has affected each school differently based on the non-pharmaceutical measures (NPMs) that school employed. Some universities used social distancing and required masks for in-person education, while others went completely online. Like other infectious diseases, COVID-19 can be modeled through an SIR model (Susceptible-Infected-Recovered). The implementation of a Decisions Support System will allow universities to make educated decisions for airborne illnesses and pandemics based on factors such as infection spread, government guidelines, and NPMs. This will provide universities with an efficient streamlined way to make educated decisions in the case of a pandemic, epidemic, or local health crisis, `so as not to significantly impact student learning or expected graduation date.

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2. Requirements

Our system was designed to help give universities like GMU a fighting chance at weathering hyper-transmissive viral outbreaks on their campus. We determined that there were a certain set of requirements that we, as students, would like to see implemented to maintain our educational rigor while also taking input from GMU's Executive Director of Safety and Emergency Management. Firstly, the primary requirement is that our system shall not allow more than 5% of each of the three university populations we defined to be infected at any given time (see Disease Model). This was a standard that we saw many universities implement anecdotally as that information was not made public. This information was gleaned from studying university response to their COVID-19 dashboard. Secondly, without reliable access to GPA data and the implementation of a pass/fail system that would skew the results, we had to look at GMU Student Evaluations of Teaching surveys in order to gauge student satisfaction with teaching delivery. This allowed us to formulate the second requirement that the decision output from the University Pandemic Response Decision Support System (UPRDSS) shall maintain 80-90% the learning quality of the most recent non-impacted semester. Thirdly, UPRDSS must be able to allow universities to make a decision in less than a month to make it a more compelling option than what universities opted to use for COVID-19.

3. Design and Methodology

We modeled our system, Figure 1, after the steps that GMU took to combat the spread of COVID-19 while also building in the flexibility for other universities to append their own requirements and tolerances. The UPRDSS is divided into three main functions: Data Collection, Disease and Learning Modelling, and Evaluation. A health crisis will trigger the need for appropriate data and the UPRDSS will initiate the Data Collection function which will intake data about the disease and learning effectiveness: infection, mortality, and recovery rates, as well as the effectiveness of non-pharmaceutical measures and historical data from student evaluation surveys. This data will then be formatted for the model and sent to the modelling component. In the modelling component the disease data will be used to run a simulation of disease spread and trends in the historical survey data will be identified. The results of these processes will be input to the decision equation and this function will output the different possible methods for disease control and the different possible methods for conducting classes. These outputs will then act as inputs to the Evaluation function which will evaluate the validity of the results and the financial feasibility of the proposed solutions.

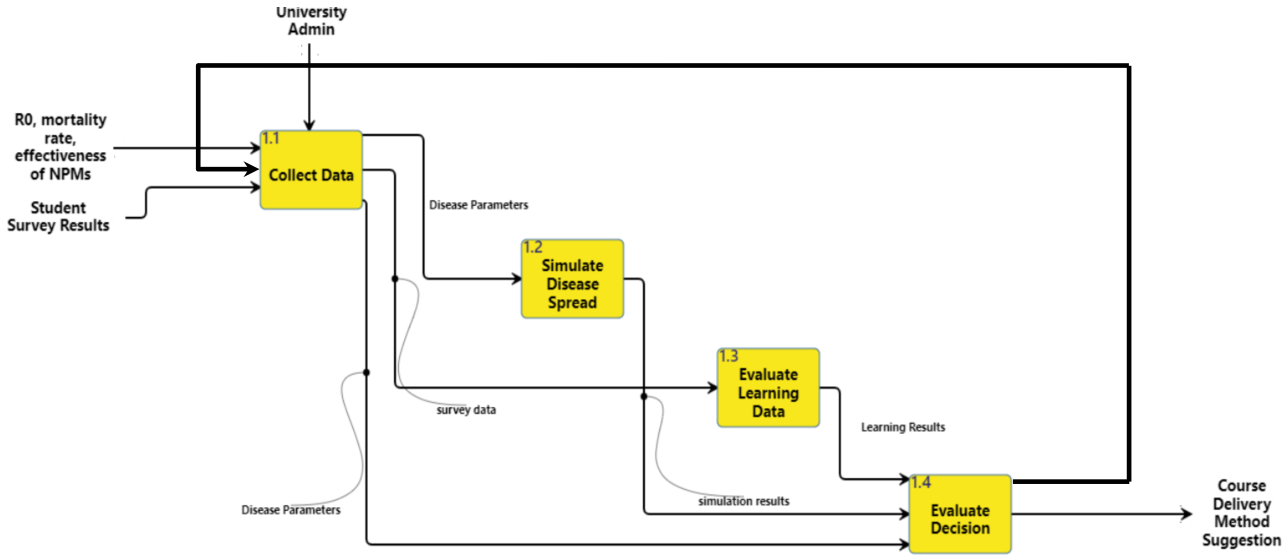

Figure 1. CONOP Main Function Block Diagram

Figure 2 shows how the system user will interact with the DSS. The main user for this system will be the university administration. They will initiate UPRDSS procedure. The UPRDSS will then send a request for learning outcome and disease data to the user. The user will need to input disease data such as infection rate, mortality rate, and NPM effectiveness as well as learning outcome data such as student evaluations of classes when they are held in person and when they are held online.

An example of how our data was appended and parsed will be available in Appendix I. Once the user inputs this data, the UPRDSS will send a receipt confirmation to the user. The system will then send a request to the user for bounds and weights, with directions for how to determine weights. The user will need to determine how they rank each of the factors involved in this decision and then input those weights to the system. The user will also need to input their upper bound, for how many cases of the disease will automatically trigger a move to online. The system will then use that information to simulate the spread of the disease and then determine which learning outcomes and which NPM can be adopted. The system will then ask the user for financial data. The user will then input financial data, such as their budget constraints. The system will then evaluate each possible disease control method and course delivery method for financial feasibility. The system will then send the results of these evaluations as well as the possible course delivery methods and possible disease control methods to the user. If the user finds these results acceptable, the user will select which option they want to go with. If the user does not find any of these results acceptable, the system will ask for new weights and run the process again.

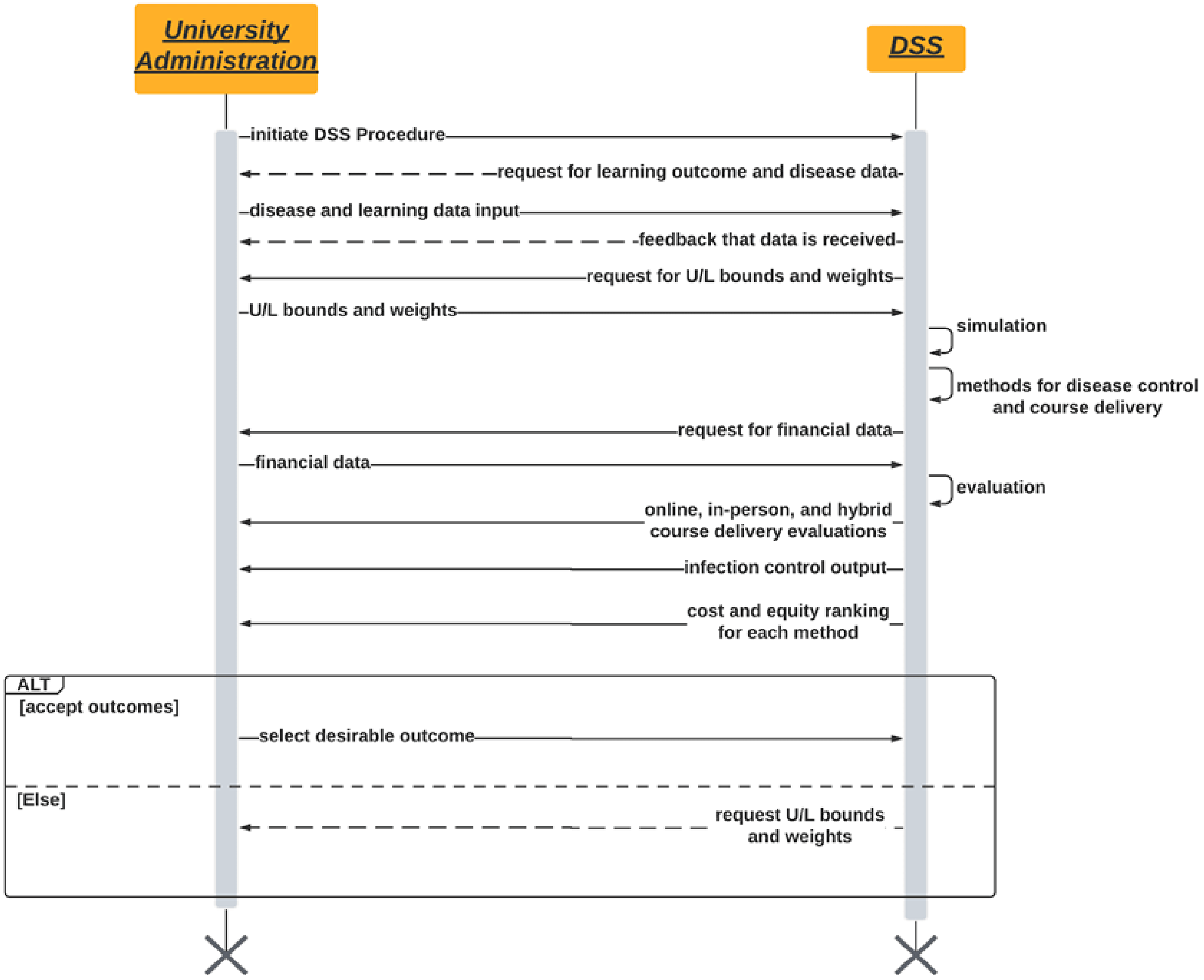

Figure 2. Sequence Diagram to initiate UPRDSS

3. Disease Model

Based on the models proposed in the literature (Bastos and Cajueiro 2020, Ghaffarzadegan 2020) we developed a SIRD dynamic systems model to simulate the spread of disease on college campuses. As shown in the flow chart in Figure 3, there are three groups, commuting students, residential students, and employees. The employee category contains both faculty and staff, however, our model groups them together because the available data does not differentiate between them.

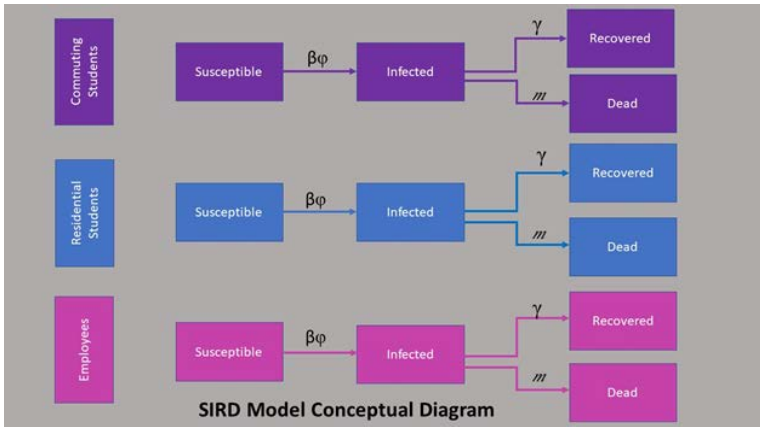

Figure 3. SIRD Conceptual Model Diagram

People in each group follow a similar path as each can be sorted into four different categories. All members of each group are originally susceptible to the disease. As they get sick, they are moved to the infected group. If individuals recover, they are moved to the recovered group, but if they die, they are moved to the dead category. As such we have twelve state variables. SC(t), SR(t), and SE(t) represent the number of commuter students, residential students, and employees who are susceptible at time t. IC(t), IR(t), and IE(t) represent the number of people in each category who are infected at time t. RC(t), RR(t), and RE(t) represent the number of people who have recovered at time t. DC(t), DR(t), and DE(t) represent the number of people who have died at time t. Our model is defined by a set of nonlinear ordinary differential equations found in Appendix II along with an explanation of the variables. Like a typical SIR model, our model assumes that people cannot get infected twice. It also assumes that faculty and staff interact with students at a similar rate, however, this is a simplification of the situation.

The model is designed to take different values for these parameters depending on the disease that is causing the pandemic. Universities can use this model to figure out the effectiveness of NPMs, such as social distancing and mask-wearing, which will ultimately help them decide if it is possible to offer in-person instruction or not. We have used these equations to build a Simulink model in MATLAB. The university can run the simulation with multiple run times to see how the disease will spread over a week, a month, a semester, or a full academic year. Used in conjunction with learning outcome data and the decision equation, this model will help universities make an informed decision about how to conduct classes.

We ran our model for George Mason University using parameters that correspond with COVID-19. About 75% of Mason's total population is commuter students, 15% is residential students, and 10% are employees. According to the CDC the average recovery time for COVID is 10 days, so we set γ to 0.1, β was set to .244, and m was set to 0.02. For our initial conditions, 100% of each group was in the susceptible category, 1 commuter student was infected, and 0 people had died of the disease. We chose to run the model with one commuter student being infected because universities can enforce testing among residential students and require that students provide a negative test before moving in. The results of this simulation are shown in Appendix VII. We then tested different values for φ as we tested the effect of different non-pharmaceutical measures. For our low safety case, we tested the effect of just having social distancing policies on campus. This does lower the peak of infection rate; however, it does not meet our mission requirement of 5% maximum infection. For our high safety case, we tested the effect of enforcing social distancing on campus as well as providing surgical masks to students and employees. This resulted in significantly lowering the peak and flattening the curve. The simulation shows that if these NPMs are enforced the infection can be controlled within a month, and the rate of infection can drop below the 5% threshold. However, universities should be cautious while making decisions based on this simulation because our model presumes that NPM guidelines are strictly followed. Unfortunately, our model cannot capture the variance and risk of infection associated with student activities off-campus.

4. Modelling Learning Outcome

According to a study conducted by Harvard University in 2018, taking online courses over in-person courses sees a reduction in student success and future progress; grades are lower for both the online course that was taken as well as sequential courses. Furthermore, the study found that students who follow this approach are less likely to remain enrolled in university

(Bettinger and Fox, 2018*)* A similar study conducted by Saint Leo University found of all the predictor variables they measured to determine a correlation between grades earned and time in online courses, only time spent in a synchronous online session showed as a significant predictor of receiving an A in the course (Carver and Muhkerjee, 2017). The trend of these values is critical to understanding the impact that COVID-19 has had on the ability for universities to transition to effective means of online education. Our own data collection using teacher evaluation surveys confirms the switch to online classes negatively impacted students' perception of the teaching quality of the class. To conduct our research, we selected a variety of classes that were deemed representative of the university as a whole and for which data was available from Fall 2018 to Summer 2020 looking specifically at Fall and Summer classes. The classes we selected included a range of required classes, elective classes, Mason CORE classes, lectures, labs, and a seminar class to gauge the impact an online semester has on wider range of class types and teaching methodology. We further decomposed our data collection by selecting a series of questions from the teacher evaluation surveys we believed were important in gauging student success and satisfaction as well as taking the given response rate and using it as an analogue for student participation in class. What we are unable to account for are the different expectations of different professors, the large class sizes (>150), and different means of survey dispersion due to the fact that we're using the student response rate to these surveys as an analogue to student participation in the classroom. In Appendix I are the calculations we conducted for reference. Given those restrictions and more time, we would refine the methodology to be aware of those discrepancies. When comparing Summer 2019, a semester that was not impacted by COVID-19, and Summer 2020, a semester that was impacted by COVID-19, 63% of classes evaluated showed a statistically significant decrease in the questions chosen to be evaluated when using Student's t-test for significance at 95%. Furthermore, a 53.7% decrease in average response rate was recorded, possibly indicating that students were disengaged in class. When we compare the same classes from Fall 2018 and Fall 2019, there is a statistically significant increase in only two classes and .28% increase in average response rate.

5. Multi-Attribute Utility Function

Since the Decision Support System must combine two main components, the disease model and the effects on learning outcome, a multi-attribute utility function can be used to determine how much each aspect affects the decision and to find the optimal solution. We came up with the following series of decision equations:

$$\mathrm{Y} = \frac{(1+kk_{infectivity}v_{infectivity}(infectivity)-1}{k} * \frac{(1+kk_{mortality}v_{mortality}(mortality)-1}{k} * \frac{(1+kk_{recovery}v_{recovery}(recovery)-1}{k} * \frac{(1+kk_{NPM}v_{NPM}(NPM)-1}{k} \tag{1}$$

$$\mathrm{Z} = \omega_{Q1}V_{Q1}(Q1) + \omega_{Q3}V_{Q3}(Q3) + \omega_{Q6}V_{Q6}(Q6) + \omega_{Q13}V_{Q13}(Q13) + \omega_{Q14}V_{Q14}(Q14) + \omega_{Q15}V_{Q15}(Q15) + \omega_{Q16}V_{Q16}(Q16) + \omega_{SR\%}V_{SR\%}(SR\%) \tag{2}$$

$$\mathrm{X} = \omega_{VIRAL}[Y] + \omega_{LEARNING}[Z] \tag{3}$$

In Equation 1 above, we measured the interactive weights between infectivity, mortality, recovery, and NPM efficacy. This was done using an HUI3 or multiplicative multi-attribute utility function. To fully understand the specifics of the equation and the process used see Appendix III. $V_i(i)$ represents the utility function for each attribute. This number is achieved by running the raw data through our compiled utility curves. These curves were set up in accordance with our mission requirements and are attached in Appendix IV. While we determined the utility functions for each attribute, the university must determine the weight for each attribute themselves as this will ensure that universities can weigh the attributes based on how they rank the importance of each attribute. In Equation 2, we used an analytical hierarchy process to determine a pairwise comparison between the questions the we selected to evaluate and their relative importance to each other. Finally, Equation 3 allows universities to 'swing the weights' to allow the UPRDSS to evaluate the criteria specific to that university. This will allow universities to calibrate the UPRDSS to prioritize either minimizing viral spread or maximizing student learning. The equations used will be available in an Excel GUI for easy access and use Appendix V. The UPRDSS will then evaluate the criteria for a High Safety Case, a Low Safety Case, and a Base Case. A High Safety Case is defined as the use of surgical masks in conjunction with social distancing employed to spread out individuals. Universities may choose to add more NPMs such as temporal distancing where certain groups of students are only allowed on campus certain days of the week, or group isolation where commuter students take online classes while residential students continue with in-person classes or any other form of NPM; our system only simulates surgical and cloth masks and social distancing as well as some combination of the former and latter. A Low Safety Case is defined as cloth masks, surgical masks, or social distancing used as an independent means of NPM in addition to a hybrid format of teaching. A Base Case is defined as no NPM deployed and a continuation of classes as they were pre-pandemic. The function with the highest utility value will be the choice dispensed to university administration. A sample sheet of the calculations is included in Appendix VI.

6. Conclusion and Future

Based on the factors that we measured and the calculations that we conducted, if GMU wanted to prioritize viral spread reduction over maximizing learning effectiveness, a High Safety Case of surgical masks and social distancing in addition to a switch to online teaching environment would be suggested by the UPRDSS until GMU prioritizes learning effectiveness at 60% versus reducing viral spread at 40%. A Low Safety Case would be suggested if GMU valued maximizing learning effectiveness at 70% versus reducing viral spread at 30%. Beyond that, if GMU prioritizes learning effectiveness at 80% versus reducing viral spread at 20%, the Base Case would be suggested which allows for in-person teaching with no NPMs or more simply, teaching pre-COVID. Our proposed DSS provides a framework for universities to take viral disease spread and the effect on student learning in to account in order to make an operations decision when responding to a pandemic, epidemic, localized health crisis. However, this DSS uses a simplified disease model and a heuristic model for learning outcomes. It can be improved by including more complexities in the disease model, such as number of students who need to quarantine, the school's capacity for quarantine, and the rate of infection in the surrounding communities as well as probabilities that suggested NPMs are followed. Universities should also invest in pedagogical studies on the effects a pandemic has on student learning as well as how to predict student learning outcomes under pandemic conditions. These studies would help us build a simulation for student learning outcomes that does not rely on historical data or heuristics, thus strengthening the Decision Support System.

7. Acknowledgments

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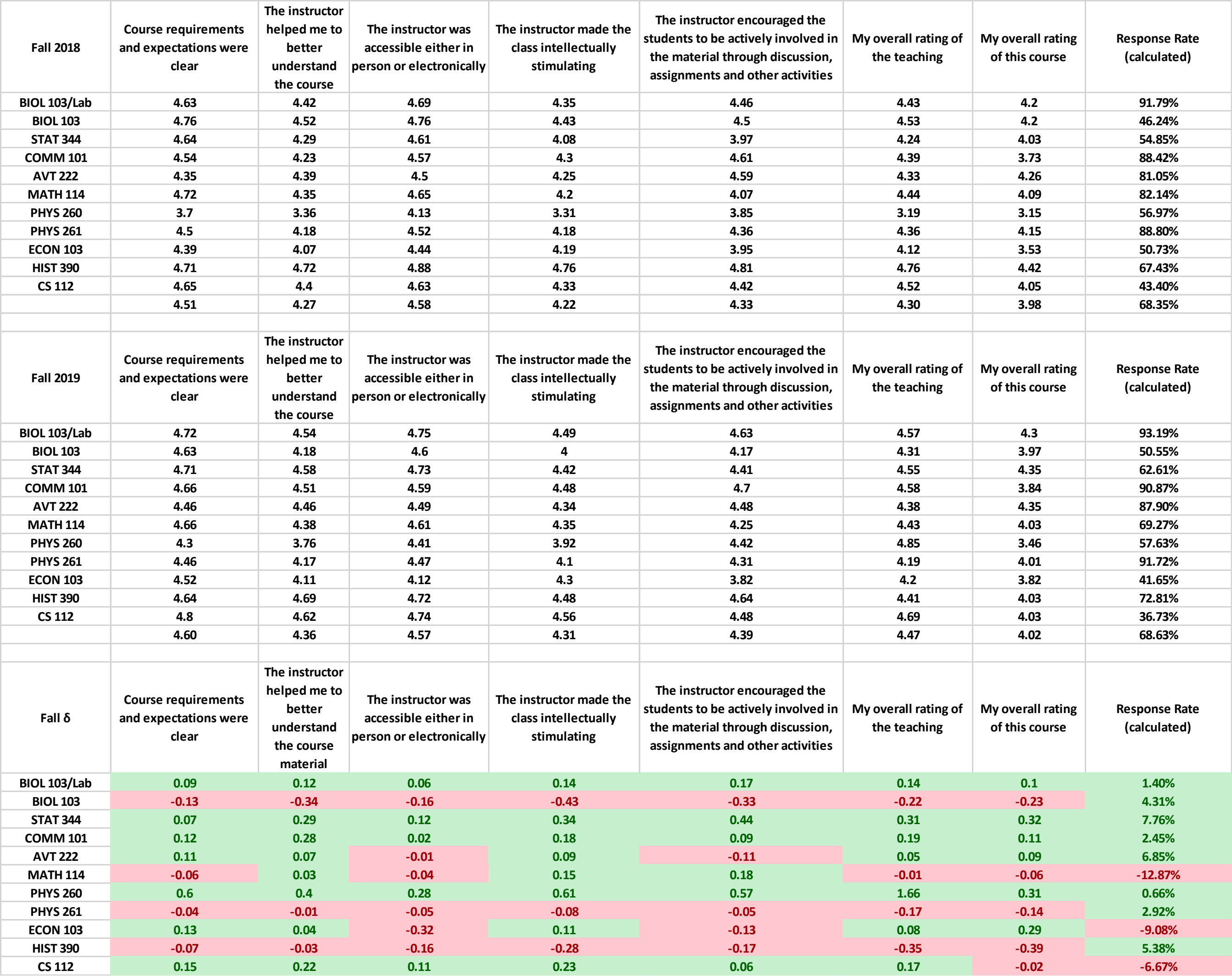
APPENDIX I

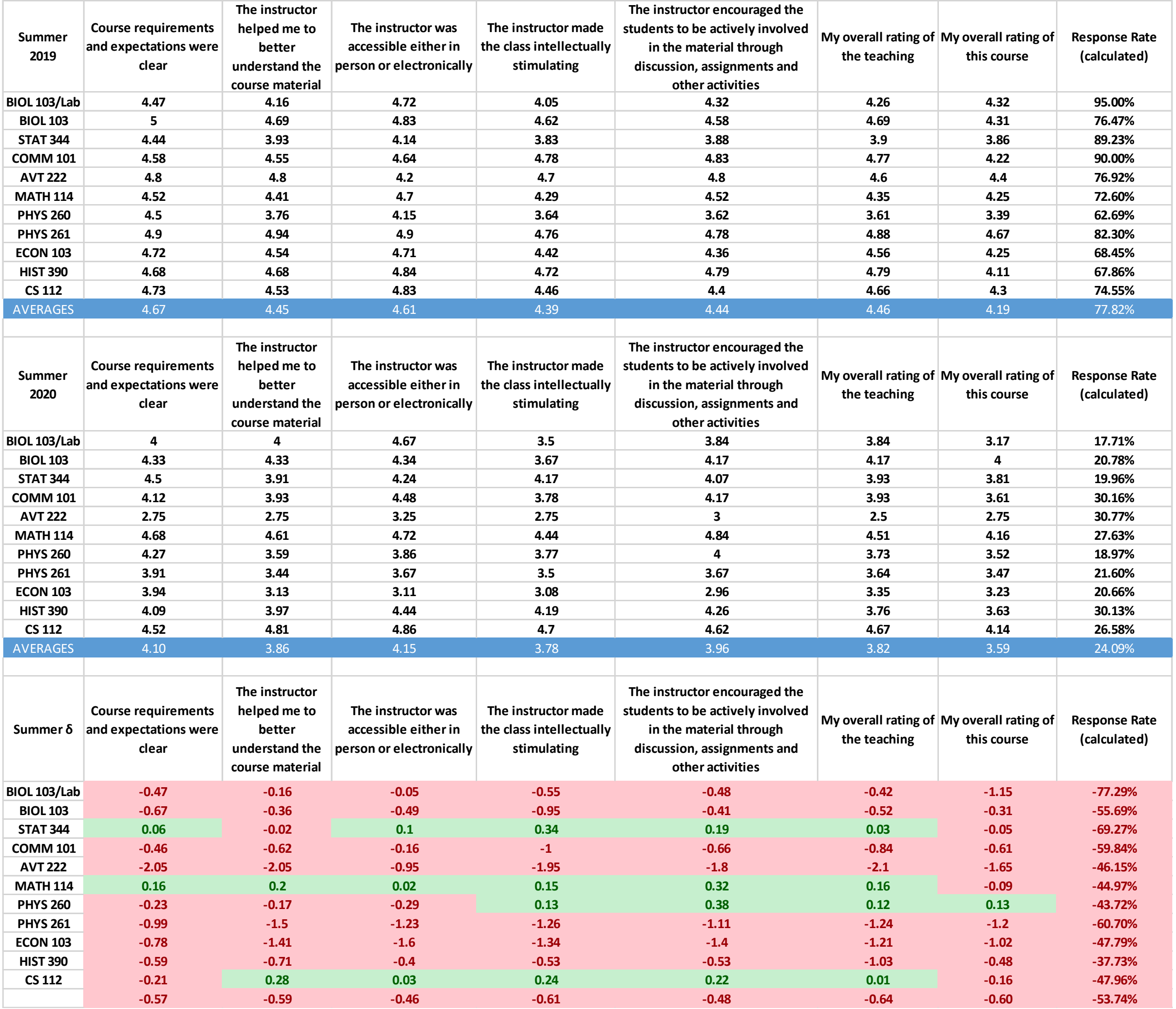


Fall 2018	Course requirements and expectations were clear	The instructor helped me to better understand the course	The instructor was accessible either in person or electronically	The instructor made the class intellectually stimulating	The instructor encouraged the students to be actively involved in the material through discussion, assignments and other activities	My overall rating of the teaching	My overall rating of this course	Response Rate (calculated)
BIOL 103/Lab	4.63	4.42	4.69	4.35	4.46	4.43	4.2	91.79%
BIOL 103	4.76	4.52	4.76	4.43	4.5	4.53	4.2	46.24%
STAT 344	4.64	4.29	4.61	4.08	3.97	4.24	4.03	54.85%
COMM 101	4.54	4.23	4.57	4.3	4.61	4.39	3.73	88.42%
AVT 222	4.35	4.39	4.5	4.25	4.59	4.33	4.26	81.05%
MATH 114	4.72	4.35	4.65	4.2	4.07	4.44	4.09	82.14%
PHYS 260	3.7	3.36	4.13	3.31	3.85	3.19	3.15	56.97%
PHYS 261	4.5	4.18	4.52	4.18	4.36	4.36	4.15	88.80%
ECON 103	4.39	4.07	4.44	4.19	3.95	4.12	3.53	50.73%
HIST 390	4.71	4.72	4.88	4.76	4.81	4.76	4.42	67.43%
CS 112	4.65	4.4	4.63	4.33	4.42	4.52	4.05	43.40%
	4.51	4.27	4.58	4.22	4.33	4.30	3.98	68.35%

Fall 2019	Course requirements and expectations were clear	The instructor helped me to better understand the course	The instructor was accessible either in person or electronically	The instructor made the class intellectually stimulating	The instructor encouraged the students to be actively involved in the material through discussion, assignments and other activities	My overall rating of the teaching	My overall rating of this course	Response Rate (calculated)
BIOL 103/Lab	4.72	4.54	4.75	4.49	4.63	4.57	4.3	93.19%
BIOL 103	4.63	4.18	4.6	4	4.17	4.31	3.97	50.55%
STAT 344	4.71	4.58	4.73	4.42	4.41	4.55	4.35	62.61%
COMM 101	4.66	4.51	4.59	4.48	4.7	4.58	3.84	90.87%
AVT 222	4.46	4.46	4.49	4.34	4.48	4.38	4.35	87.90%
MATH 114	4.66	4.38	4.61	4.35	4.25	4.43	4.03	69.27%
PHYS 260	4.3	3.76	4.41	3.92	4.42	4.85	3.46	57.63%
PHYS 261	4.46	4.17	4.47	4.1	4.31	4.19	4.01	91.72%
ECON 103	4.52	4.11	4.12	4.3	3.82	4.2	3.82	41.65%
HIST 390	4.64	4.69	4.72	4.48	4.64	4.41	4.03	72.81%
CS 112	4.8	4.62	4.74	4.56	4.48	4.69	4.03	36.73%
	4.60	4.36	4.57	4.31	4.39	4.47	4.02	68.63%

Fall δ	Course requirements and expectations were clear	The instructor helped me to better understand the course material	The instructor was accessible either in person or electronically	The instructor made the class intellectually stimulating	The instructor encouraged the students to be actively involved in the material through discussion, assignments and other activities	My overall rating of the teaching	My overall rating of this course	Response Rate (calculated)
BIOL 103/Lab	0.09	0.12	0.06	0.14	0.17	0.14	0.1	1.40%
BIOL 103	-0.13	-0.34	-0.16	-0.43	-0.33	-0.22	-0.23	4.31%
STAT 344	0.07	0.29	0.12	0.34	0.44	0.31	0.32	7.76%
COMM 101	0.12	0.28	0.02	0.18	0.09	0.19	0.11	2.45%
AVT 222	0.11	0.07	-0.01	0.09	-0.11	0.05	0.09	6.85%
MATH 114	-0.06	0.03	-0.04	0.15	0.18	-0.01	-0.06	-12.87%
PHYS 260	0.6	0.4	0.28	0.61	0.57	1.66	0.31	0.66%
PHYS 261	-0.04	-0.01	-0.05	-0.08	-0.05	-0.17	-0.14	2.92%
ECON 103	0.13	0.04	-0.32	0.11	-0.13	0.08	0.29	-9.08%
HIST 390	-0.07	-0.03	-0.16	-0.28	-0.17	-0.35	-0.39	5.38%
CS 112	0.15	0.22	0.11	0.23	0.06	0.17	-0.02	-6.67%

These values represent Fall 2018 and Fall 2019. In the two uppermost tables are the average ratings per question we evaluated for all sections of a particular class. The bottommost table is the δ between the two. This shows that there is background variance in this method of measurement and with more data from more semesters, a robust trendline can be developed.



Summer 2019	Course requirements and expectations were clear	The instructor helped me to better understand the course material	The instructor was accessible either in person or electronically	The instructor made the class intellectually stimulating	The instructor encouraged the students to be actively involved in the material through discussion, assignments and other activities	My overall rating of the teaching	My overall rating of this course	Response Rate (calculated)
BIOL 103/Lab	4.47	4.16	4.72	4.05	4.32	4.26	4.32	95.00%
BIOL 103	5	4.69	4.83	4.62	4.58	4.69	4.31	76.47%
STAT 344	4.44	3.93	4.14	3.83	3.88	3.9	3.86	89.23%
COMM 101	4.58	4.55	4.64	4.78	4.83	4.77	4.22	90.00%
AVT 222	4.8	4.8	4.2	4.7	4.8	4.6	4.4	76.92%
MATH 114	4.52	4.41	4.7	4.29	4.52	4.35	4.25	72.60%
PHYS 260	4.5	3.76	4.15	3.64	3.62	3.61	3.39	62.69%
PHYS 261	4.9	4.94	4.9	4.76	4.78	4.88	4.67	82.30%
ECON 103	4.72	4.54	4.71	4.42	4.36	4.56	4.25	68.45%
HIST 390	4.68	4.68	4.84	4.72	4.79	4.79	4.11	67.86%
CS 112	4.73	4.53	4.83	4.46	4.4	4.66	4.3	74.55%
AVERAGES	4.67	4.45	4.61	4.39	4.44	4.46	4.19	77.82%

Summer 2020	Course requirements and expectations were clear	The instructor helped me to better understand the course material	The instructor was accessible either in person or electronically	The instructor made the class intellectually stimulating	The instructor encouraged the students to be actively involved in the material through discussion, assignments and other activities	My overall rating of the teaching	My overall rating of this course	Response Rate (calculated)
BIOL 103/Lab	4	4	4.67	3.5	3.84	3.84	3.17	17.71%
BIOL 103	4.33	4.33	4.34	3.67	4.17	4.17	4	20.78%
STAT 344	4.5	3.91	4.24	4.17	4.07	3.93	3.81	19.96%
COMM 101	4.12	3.93	4.48	3.78	4.17	3.93	3.61	30.16%
AVT 222	2.75	2.75	3.25	2.75	3	2.5	2.75	30.77%
MATH 114	4.68	4.61	4.72	4.44	4.84	4.51	4.16	27.63%
PHYS 260	4.27	3.59	3.86	3.77	4	3.73	3.52	18.97%
PHYS 261	3.91	3.44	3.67	3.5	3.67	3.64	3.47	21.60%
ECON 103	3.94	3.13	3.11	3.08	2.96	3.35	3.23	20.66%
HIST 390	4.09	3.97	4.44	4.19	4.26	3.76	3.63	30.13%
CS 112	4.52	4.81	4.86	4.7	4.62	4.67	4.14	26.58%
AVERAGES	4.10	3.86	4.15	3.78	3.96	3.82	3.59	24.09%

Summer δ	Course requirements and expectations were clear	The instructor helped me to better understand the course material	The instructor was accessible either in person or electronically	The instructor made the class intellectually stimulating	The instructor encouraged the students to be actively involved in the material through discussion, assignments and other activities	My overall rating of the teaching	My overall rating of this course	Response Rate (calculated)
BIOL 103/Lab	-0.47	-0.16	-0.05	-0.55	-0.48	-0.42	-1.15	-77.29%
BIOL 103	-0.67	-0.36	-0.49	-0.95	-0.41	-0.52	-0.31	-55.69%
STAT 344	0.06	-0.02	0.1	0.34	0.19	0.03	-0.05	-69.27%
COMM 101	-0.46	-0.62	-0.16	-1	-0.66	-0.84	-0.61	-59.84%
AVT 222	-2.05	-2.05	-0.95	-1.95	-1.8	-2.1	-1.65	-46.15%
MATH 114	0.16	0.2	0.02	0.15	0.32	0.16	-0.09	-44.97%
PHYS 260	-0.23	-0.17	-0.29	0.13	0.38	0.12	0.13	-43.72%
PHYS 261	-0.99	-1.5	-1.23	-1.26	-1.11	-1.24	-1.2	-60.70%
ECON 103	-0.78	-1.41	-1.6	-1.34	-1.4	-1.21	-1.02	-47.79%
HIST 390	-0.59	-0.71	-0.4	-0.53	-0.53	-1.03	-0.48	-37.73%
CS 112	-0.21	0.28	0.03	0.24	0.22	0.01	-0.16	-47.96%
	-0.57	-0.59	-0.46	-0.61	-0.48	-0.64	-0.60	-53.74%

These values represent Summer 2019, a non-COVID semester, and Summer 2020, a COVID semester. In the two uppermost tables are the average ratings per question we evaluated for all sections of a particular class. The bottommost table is the δ between the two. This validates that there is a need for a system the preserves academic rigor and teaching effectiveness.

APPENDIX II

Commuter Student Equations	
Susceptible	$S_C'(t) = -\beta\varphi S_C I_V - \varphi\ \delta S_C I_R - \varphi\delta S_C I_E - vS_C$
Infected	$I_C'(t) = \beta S_C I_C + \varphi\delta S_C I_R + \varphi\delta S_C I_E - \gamma I_C - mI_C$
Recovered	$R_C'(t) = \gamma I_C + vS_C$
Dead	$D_C'(t) = mI_C$

Residential Student Equations	
Susceptible	$S_R'(t) = -\beta\varphi S_R I_R - \varphi\ \delta S_R I_C - \varphi\delta S_R I_E - vS_R$
Infected	$I_R'(t) = \beta S_R I_R + \varphi\delta S_R I_C + \varphi\delta S_R I_E - \gamma I_R - mI_R$
Recovered	$R_R'(t) = \gamma I_R + vS_R$
Dead	$D_R'(t) = mI_R$

Employee Equations	
Susceptible	$S_E'(t) = -\beta\varphi S_E I_E - \varphi\ \delta S_E I_C - \varphi\delta S_E I_R - vS_E$
Infected	$I_E'(t) = \beta S_E I_E + \varphi\delta S_E I_C + \varphi\delta S_E I_R - \gamma I_E - mI_E$
Recovered	$R_E'(t) = \gamma I_E + vS_E$
Dead	$D_E'(t) = mI_E$

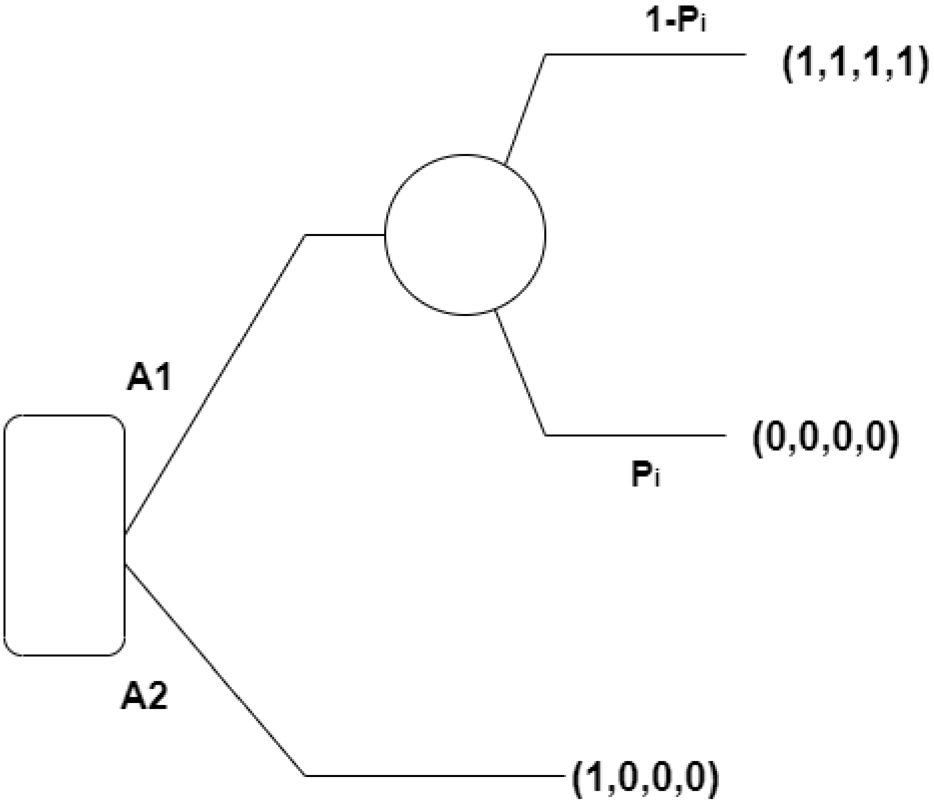
Above are the equations associated with our viral model

Mathematical Symbol	Description
m	The mortality rate of the disease.
ϕ	The effect of NPMs on rate of transmission. This value can vary between 0 and 1, where smaller values represent a stronger effect on the rate of transmission. When NPMs are not in place we will set ϕ equal to 1.
γ	The rate of recovery. The rate of recovery is defined as the amount of time it takes for a person to stop being infectious. As such, recovery rate is equal to the reciprocal of the infectious period.
β	The rate of transmission. In a typical SIR model β/ɣ is equal to the basic reproduction number (R0) of the disease. Based on that information β can be calculated from the values for R0 and ɣ.
δ	The interaction between members of different groups.
v	The percent of people who have been vaccinated against the disease.

Above are the descriptions associated with each variable

APPENDIX III

We worked on the Multi Attribute function method. We gathered all of the factors that we are trying to find the value of which are, infectivity , Mortality, Recovery rate in days, and NPM effectiveness.

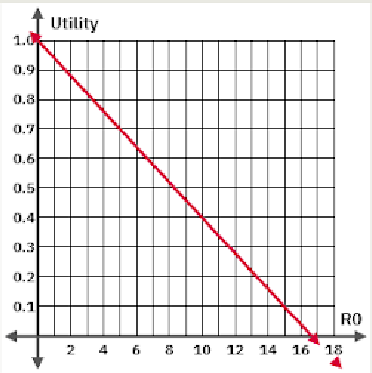


In our modeling we came up with an estimated number for each of the values of the factors.

Infectivity = k1 = 0.05
Mortality = k2 = 0.02
Recovery = k3 = 0.5
Non Pharmaceutical Measure Effectiveness (NPM) = k4 = 0.4

In the uppermost part of the diagram, there's the likelihood that everything goes right, hence all the 1s. Below that, is the likelihood that everything goes wrong. In the case of the UPRDSS, this indicates that the R0 value meets or exceeds 18, mortality rate is greater than or equal to 25%, the recovery period is greater than 30 days, and NPM are not effective means of reducing the viral spread; hence why the values are 0. The bottommost branch of the tree is iterative and the value of 1 moves in correspondence to the variable we're measuring. In the above example, we're looking at infectivity, hence 1 is in the first position. If we were to look at the recovery rate, then the 1 would be in the third position. This bottommost branch shows the certainty that everything will go wrong aside from the variable that we're measuring which again in the case of the example above is infectivity. The purpose of this tree shows that we can make a decision, A1 or A2, where A1 holds an inherent risk of Pi. We must find a value of Pi that makes us indifferent to the paths A1 or A2.

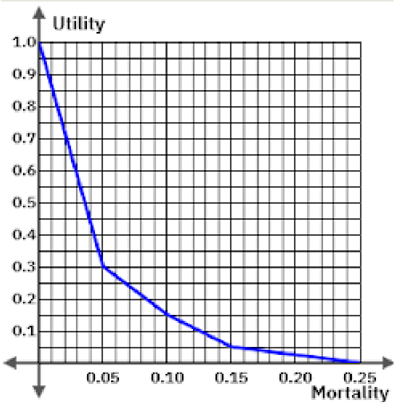
APPENDIX IV



Infectivity Utility Curve

y = −0.0555555555555555x + 1

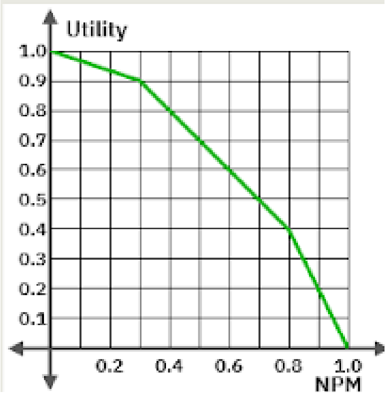
We use R_0 as the x value in spite of its limitations. This allows the system to react when there are no known deterrents ie. when an outbreak occurs and the world is unprepared like during Ebola, Zika, and COVID-19



Mortality Utility Curve

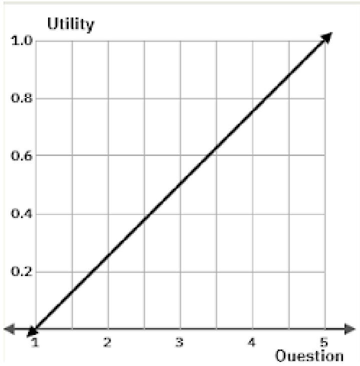
y = -14x + 1 if x < .05
y = -3x + .45 if .05 <= x < .1
y = -2x + .35 if .1 <= x < .15
y = -.5x + .125 if x >= .15

The upper limit of acceptable mortality for our system is 25%. Above that, the utility is zero.



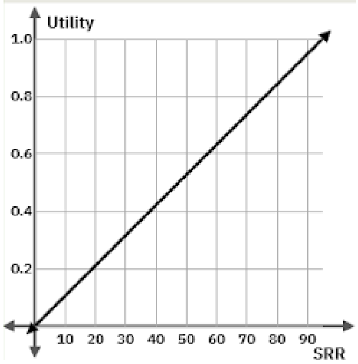
NPM Effectiveness Utility Curve

y = -.33x + 1 if x < .3
y = -x + 1.2 if .3 <= x < .8
y = -2x + 2 if x >= .8



Question Value Utility Curve

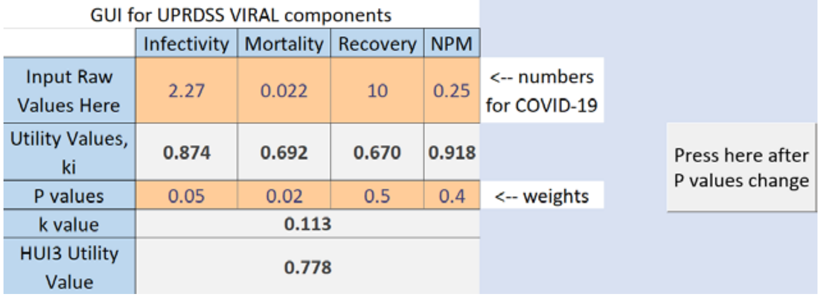
y = .25x-.25



Survey Response Rate Utility Curve

y = 1/95x

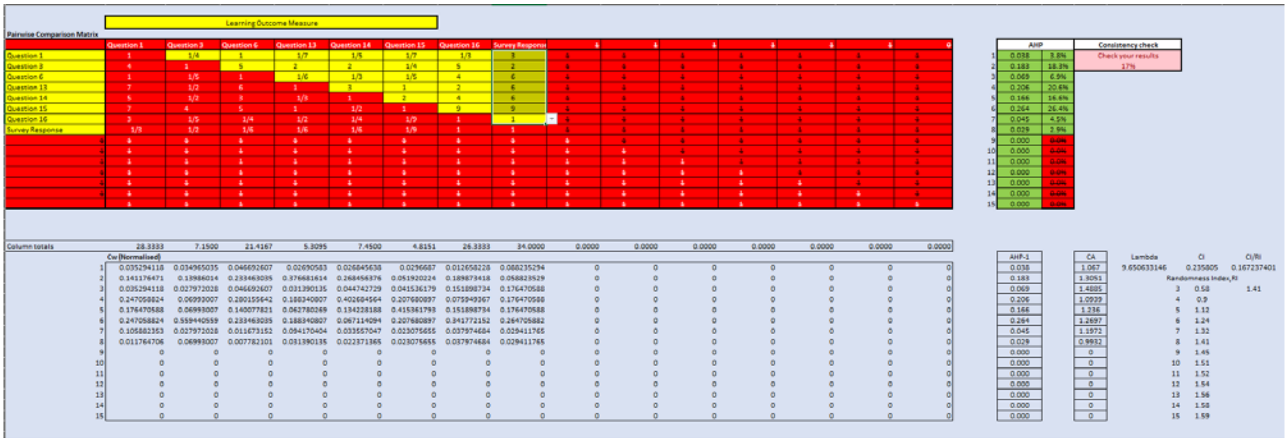
APPENDIX V



GUI for UPRDSS VIRAL components

	Infectivity	Mortality	Recovery	NPM	
Input Raw Values Here	2.27	0.022	10	0.25	<-- numbers for COVID-19
Utility Values, ki	**0.874**	**0.692**	**0.670**	**0.918**	
P values	0.05	0.02	0.5	0.4	<-- weights
k value	**0.113**				
HUI3 Utility Value	**0.778**				

VIRAL HUI3 Calculation GUI



Learning Outcome Measure

Pairwise Comparison Matrix

	Question 1	Question 3	Question 6	Question 13	Question 14	Question 15	Question 16	Survey Response
Question 1	1	1/4	1	1/7	1/5	1/7	1/3	3
Question 3	4	1	5	2	2	1/4	5	2
Question 6	1	1/5	1	1/6	1/3	1/5	4	6
Question 13	7	1/2	6	1	3	1	2	6
Question 14	5	1/2	3	1/3	1	2	4	6
Question 15	7	4	5	1	1/2	1	9	9
Question 16	3	1/5	1/4	1/2	1/4	1/9	1	1
Survey Response	1/3	1/2	1/6	1/6	1/6	1/9	1	1

Column totals: 28.3333, 7.1500, 21.4167, 5.3095, 7.4500, 4.8151, 26.3333, 34.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000, 0.0000

Cw (Normalised)

1	0.035294118	0.034965035	0.046692607	0.02690583	0.026845638	0.0296687	0.012658228	0.088235294
2	0.141176471	0.13986014	0.233463035	0.376681614	0.268456376	0.051920224	0.189873418	0.058823529
3	0.035294118	0.027972028	0.046692607	0.031390135	0.044742729	0.041536179	0.151898734	0.176470588
4	0.247058824	0.06993007	0.280155642	0.188340807	0.402684564	0.207680897	0.075949367	0.176470588
5	0.176470588	0.06993007	0.140077821	0.062780269	0.134228188	0.415361793	0.151898734	0.176470588
6	0.247058824	0.559440559	0.233463035	0.188340807	0.067114094	0.207680897	0.341772152	0.264705882
7	0.105882353	0.027972028	0.011673152	0.094170404	0.033557047	0.023075655	0.037974684	0.029411765
8	0.011764706	0.06993007	0.007782101	0.031390135	0.022371365	0.023075655	0.037974684	0.029411765
9	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0

	AHP		Consistency check
1	0.038	3.8%	Check your results 17%
2	0.183	18.3%	
3	0.069	6.9%	
4	0.206	20.6%	
5	0.166	16.6%	
6	0.264	26.4%	
7	0.045	4.5%	
8	0.029	2.9%	
9	0.000	0.0%	
10	0.000	0.0%	
11	0.000	0.0%	
12	0.000	0.0%	
13	0.000	0.0%	
14	0.000	0.0%	
15	0.000	0.0%	

AHP-1	CA
0.038	1.067
0.183	1.3051
0.069	1.4885
0.206	1.0939
0.166	1.236
0.264	1.2697
0.045	1.1972
0.029	0.9932
0.000	0
0.000	0
0.000	0
0.000	0
0.000	0
0.000	0
0.000	0

Lambda	CI	CI/RI
9.650633146	0.235805	0.167237401

Randomness Index, RI

3	0.58	1.41
4	0.9	
5	1.12	
6	1.24	
7	1.32	
8	1.41	
9	1.45	
10	1.51	
11	1.52	
12	1.54	
13	1.56	
14	1.58	
15	1.59	

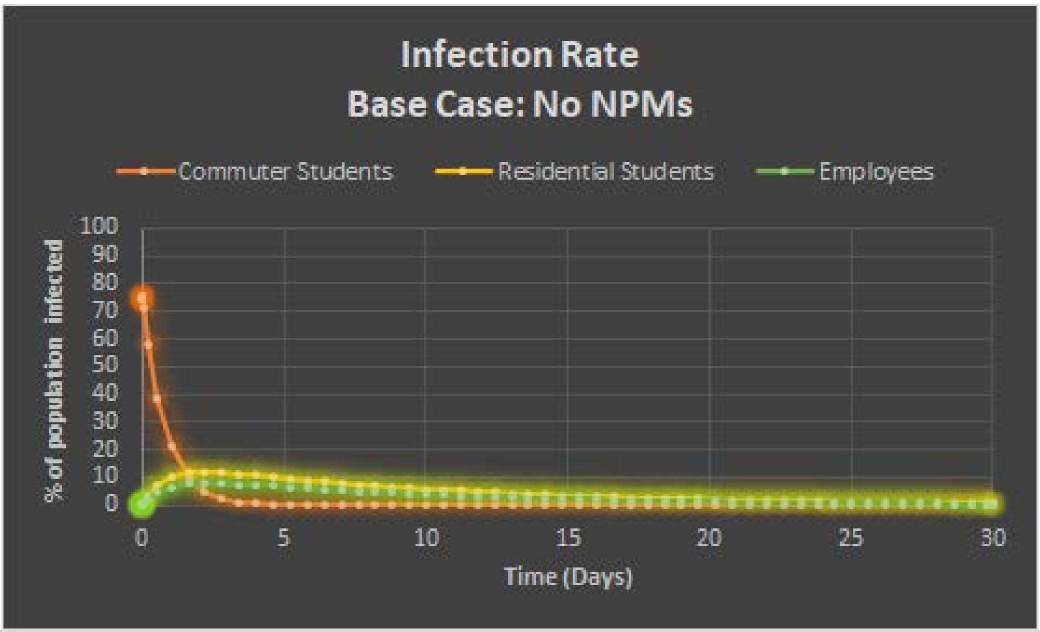
LEARNING AHP Calculation GUI

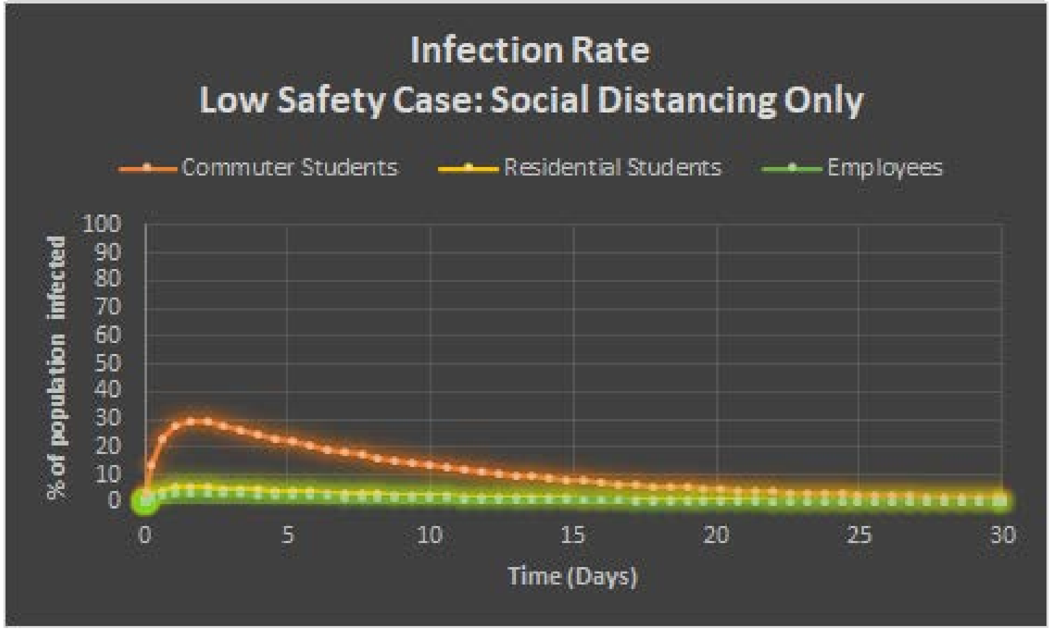
APPENDIX VI

		VIRAL		LEARNING			Comparative Values: The higher the utility value, the more evidence there is to select that safety case
Cluster 1	High	0.9	0.778	0.1	0.6961	0.76981	
	Low	0.9	0.617	0.1	0.7782	0.63312	
	Base	0.9	0.394	0.1	0.8603	0.44063	
Cluster 2	High	0.8	0.778	0.2	0.6961	0.76162	
	Low	0.8	0.617	0.2	0.7782	0.64924	
	Base	0.8	0.394	0.2	0.8603	0.48726	
Cluster 3	High	0.7	0.778	0.3	0.6961	0.75343	
	Low	0.7	0.617	0.3	0.7782	0.66536	
	Base	0.7	0.394	0.3	0.8603	0.53389	
Cluster 4	High	0.6	0.778	0.4	0.6961	0.74524	
	Low	0.6	0.617	0.4	0.7782	0.68148	
	Base	0.6	0.394	0.4	0.8603	0.58052	
Cluster 5	High	0.5	0.778	0.5	0.6961	0.73705	
	Low	0.5	0.617	0.5	0.7782	0.6976	
	Base	0.5	0.394	0.5	0.8603	0.62715	
Cluster 6	High	0.4	0.778	0.6	0.6961	0.72886	
	Low	0.4	0.617	0.6	0.7782	0.71372	
	Base	0.4	0.394	0.6	0.8603	0.67378	
Cluster 7	High	0.3	0.778	0.7	0.6961	0.72067	
	Low	0.3	0.617	0.7	0.7782	0.72984	
	Base	0.3	0.394	0.7	0.8603	0.72041	
Cluster 8	High	0.2	0.778	0.8	0.6961	0.71248	
	Low	0.2	0.617	0.8	0.7782	0.74596	
	Base	0.2	0.394	0.8	0.8603	0.76704	
Cluster 9	High	0.1	0.778	0.9	0.6961	0.70429	
	Low	0.1	0.617	0.9	0.7782	0.76208	
	Base	0.1	0.394	0.9	0.8603	0.81367	

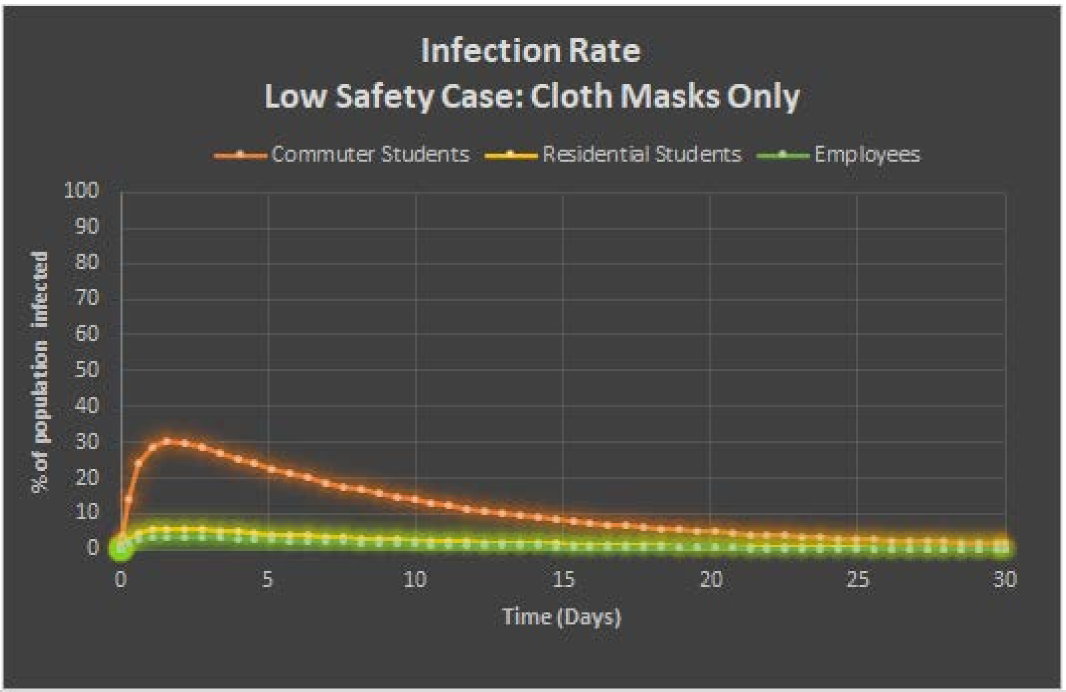
These are the utility values associated with the numbers we got for GMU as well as the weights universities can potentially assign the decision equation. Each cluster defines a set of weights a university might assign to each component of the decision equation. The highest value in each cluster is the suggested course of action for a university to pursue given their inputs.

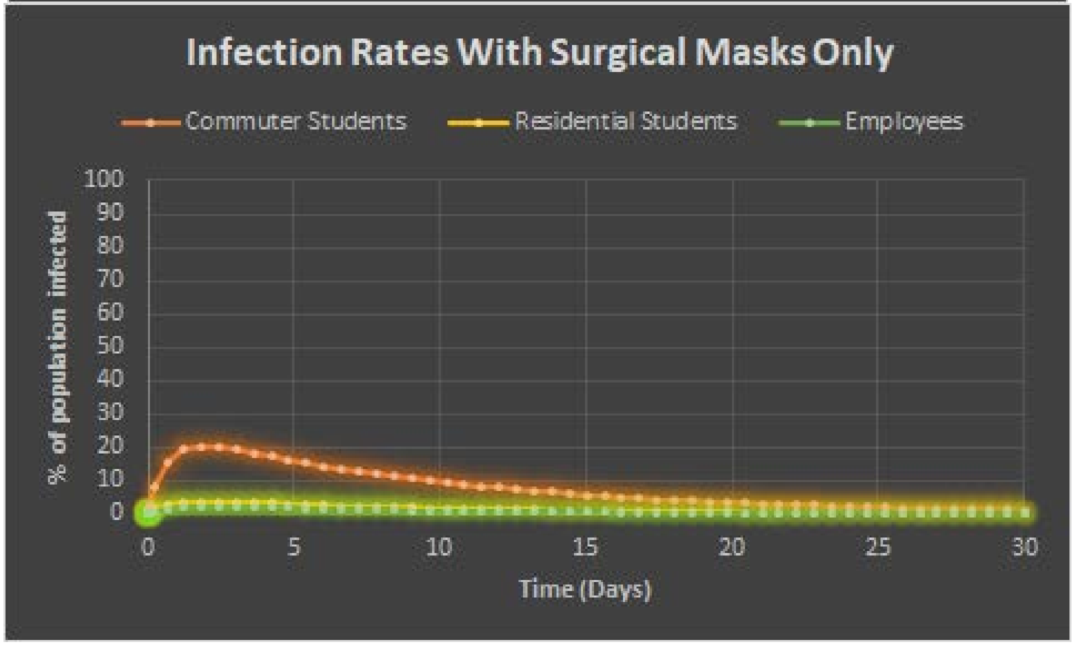
APPENDIX VII





APPENDIX VII cont.





APPENDIX VII cont.