Engineering a Resilient Healthcare System:
Development of an Agent-Based Model to Improve Heart Attack Outcomes in Pennsylvania

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Nathan Edwards, MITRE

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Abstract

Healthcare systems often become overwhelmed due to external circumstances such as the COVID-19 pandemic. Due to fluctuating circumstances, an overflow of patients along with limited resources has caused a decrease in quality and frequency of care for other patients. The goal of this project is to focus on healthcare systems for cardiovascular patients in Pennsylvania. This project uses agent based simulation to create a visualization of hospital flow for heart-attack patients in Pennsylvania hospitals by using data from a representative sample from 3 hospitals. Alternatives for hospital operations will then be proposed and applied to the simulation to identify hospital efficiency, especially under stress. The overall goal of the project is to improve the healthcare system in Pennsylvania through the use of algorithms that will identify efficacy for proposed alternatives. In summation of our results, telehealth, teletriage, and the addition of co-located clinics all decrease (improve) mortality rates from heart attacks in urban and suburban hospitals. It is seen that teletriage and telehealth have a greater impact on minimizing mortality rates when compared to the addition of clinics.

Keywords: Heart Attack, Healthcare Outcomes, Agent Based Simulation, Hospital Operations

Introduction

There are significant gaps in current healthcare delivery models that require patients to receive non-emergent, routine, or preventative care at fixed facilities. These gaps include a lack of alternative options such as telemedicine or at-home care [1]. When the healthcare system is strained with fluctuating circumstances such as a pandemic or regional disaster, a larger influx of non-emergent patients to fixed facilities can result in bottlenecks and a failure to deliver basic needs to portions of the patient population. At the same time some regional medical resources may sit idle. Bouillon-Minois et al. describes how an increased demand for healthcare decreases hospital beds and staff size, which led to overcrowding in the Emergency Department. This has become a significant public health problem over the last decade. This situation was exacerbated by the outbreak of COVID-19, which resulted in a 58% increase in overcrowding in 2020 [2]. Therefore, a study of healthcare resilience, the ability of a healthcare system to adapt to outside stressors without a significant decrease in efficiency, is crucial in order to develop healthcare delivery models that can handle stressful events like a pandemic [3].

One of the most significant conditions that healthcare systems are faced with is cardiovascular disease, which is the leading cause of death in the United States [4]. Every year, more than 800,000 Americans suffer from a heart attack and about 12% of these annual heart attacks are fatal [5] [6]. Cardiovascular disease is caused and exacerbated by many social determinants and lifestyle choices. Additionally, it was noted that during a heart attack, rapid treatment is critical to prevent patient death. However, heart attack prevention and care are not efficient or adequate across the United States. In 2017, the highest cause of death in Pennsylvania was heart attacks and heart disease. Overall, the state is ranked 14th in heart disease death when ranked from highest to lowest death rate [7]. This is notable particularly because of a study done by the U.S. News & World Report, who evaluated over 4,500 hospitals in the United States to determine the best ones. Within this report, only 134 hospitals were ranked top in at least one specialty. In this report, 26 hospitals that were ranked were located in Pennsylvania [8]; this is indicative of a viable hospital system within the state that does not match the heart attack mortality rates. Therefore, our team's first aim was to apply an operations research approach to evaluate and remodel Pennsylvania's healthcare system for heart attack patients to improve efficiency and resiliency. Using operations research methods allowed us to measure the current efficiency and resiliency of the healthcare system in Pennsylvania, particularly hospitals, for heart attack patients and analyze alternative healthcare resources, such as telemedicine or at-home care, to suggest ways to improve this system, which was our second aim. The method used in this report is Agent Based Modeling using Netlogo. Models were made for three hospital systems in Pennsylvania to simulate the flow of patients through the hospital while receiving treatment. The model was beneficial to visualize patient timelines. It also obtained outcomes based on the addition of extra healthcare resources such as telehealth/teletriage and clinics to determine the impact on 5 various factors: heart attack deaths, other emergent deaths, percent of patients treated, percent of patients turned away, and average patient wait time. We hypothesized that these 5 outcomes can be improved by the addition of telehealth and/or a co-located primary clinic to reduce emergency department crowding.

Results

Baseline Model (no new additional resources)

Allegheny Hospital (Urban)

Multiple of the output variables are compared in regards to hospital (location type) and model type (baseline or the improved models). In the Allegheny hospital baseline model, fluctuations in patient outcomes did not occur until the patient arrival was set to a high rate (6 patients every 15 minutes). The number of deaths remained at 0 ± 0 when the patient arrival rates were at low (2 patients every 15 minutes) and middle (4 patients every 15 minutes) and increased significantly at a high patient arrival rate to 101.75 ± 11.98. It was at this high rate that the average wait time remained the same, but there were many fluctuations for individual patients. This could be because the lengthiest process in the hospital is recovery time for critical patients, which is 6.5 days. Therefore, bottlenecks occur periodically as the inpatient unit fills up, spiking the wait time, and does not clear until those patients are discharged. Additionally, the high patient arrival rate is the only rate that caused patient death at a stepwise increase. The percent of patients ignored and the percent of patients treated are relatively similar across various patient arrival rates.

Armstrong Hospital (Rural)

Armstrong's baseline model represents our rural hospital data set. As a result, the low patient arrival rate placed stress on the system. Spikes in wait times similar to those in the Allegheny graphs at high patient arrivals were visible at the middle patient arrival rate, which was different than the other hospitals. Additionally, no patients were turned away in the low arrival rate scenario (1 patient every 15 minutes) but about 40% were turned away in the middle arrival rate (1 patient every 15 minutes), dropping the percentage of patients treated from about 90% to about 50%. However, deaths (both heart attack and other) were visible at both arrivals (low and middle) although the number of deaths was visibly higher at the middle patient arrival rate. The rate of increase of deaths appears more consistent, rather than showing the stepwise pattern in the Allegheny. This may be due to the fact that the Armstrong inpatient and transfer capacities are significantly smaller, allowing bottlenecks and therefore deaths to occur faster and more consistently.

Forbes Hospital (Suburban)

The Forbes hospital baseline model also began to show patient death at its high rate (3 patients every 15 minutes) in a stepwise increase; however, the rate of death increase was larger at 132.5 ± 5.4467 in comparison to Allegheny's heart attack death rate of 101.75 ± 11.9826. The Forbes model had a similar stepwise pattern in the rate of increase of deaths to that of Allegheny and unlike the consistent pattern in the Armstrong data. The percent of patients treated and percent of patients ignored were similar across the different patient arrival rates, which was a similar trend to that of the other hospitals as well. The percent of patients turned away remained low across patient arrival rates. This value for Armstrong and Allegheny were similar to each other in comparison to Forbes, but all were still relatively low. Average wait time had a substantial increase at a high patient arrival rate, which is different from that of the other hospital types.

Addition of Teletriage and Telehealth

Allegheny Hospital (Urban)

As expected, increasing teletriage/telehealth capacity exponentially increased percent of patients treated in the middle and high patient arrival scenarios (Figure 1). At the middle and high patient arrival rates, increasing teletriage and telehealth capacity decreased the amount of patients turned away from the emergency department. This decrease of patients turned away was exponential, with percent of patients turned away decreasing rapidly at even small capacities.

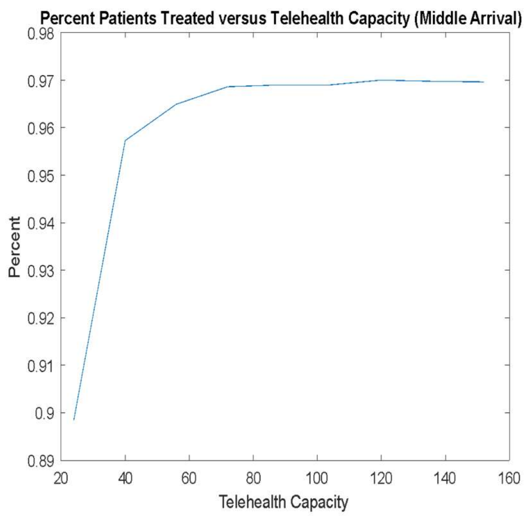


Figure 1A: Percent patients treated versus the telehealth capacity in the model for the Allegheny hospital with the medium arrival rate.

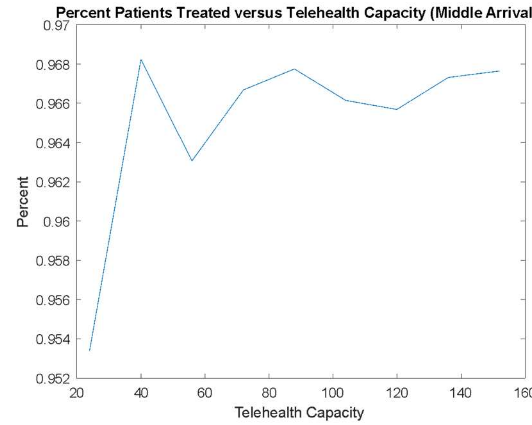


Figure 1B: Percent patients treated versus the telehealth capacity in the model for the Forbes hospital with the medium arrival rate.

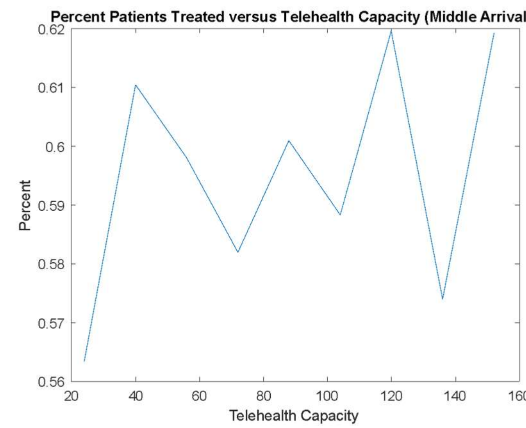


Figure 1C: Percent patients treated versus the telehealth capacity in the model for the Armstrong hospital with the medium arrival rate.

Armstrong Hospital (Rural)

In this dataset, the variables fluctuated across the telehealth capacity, but the net change was close, if not to 0. The percent of patients ignored did not increase or decrease across the various capacity rates. Average wait time relatively decreased with the low capacity, but was decreasing at a decreasing rate with the middle and high capacity. It seems that the patient arrival rate has a higher impact on average wait times and the telehealth capacity couldn't keep up with this influx. Patients turned away decreased with telehealth capacity addition across all arrival rates. The number of deaths remained the same for low patient arrival rate, decreased for middle, but decreased then increased for high. This shows that in the rural hospital, the addition of telehealth works so far before the patient arrival rate becomes too much. The percent of patients treated when teletriage and telehealth capacity increased. When this capacity was increased, percent of patients treated did not visibly increase. However, the percent of patients turned away did decrease. An explanation for this outcome is that the higher number of deaths occurring in the Armstrong model had a greater impact on the percent of patients treated than those that were turned away.

Forbes Hospital (Suburban)

Similar to Allegheny Hospital, this modification increased percent of patients treated in the middle and high patient arrival scenarios.The introduction of teletriage and telehealth did not improve percent of patients ignored, average wait times, or number of deaths. The reason for this was that the teletriage and telehealth capacity increasingly filled up at all of the patient arrival rates (low, middle, high).

Addition of Clinics

Allegheny Hospital (Urban)

In the Allegheny hospital (urban), similar to telehealth/teletriage model, as the clinic capacity increased, the percent of patients turned away decreased exponentially and percent of patients treated increased exponentially in the middle and high patient arrival rate scenarios. For the low patient arrival rate, no patients were turned away, regardless of the clinic capacity. Unlike the teletriage/telehealth model, at a high patient arrival rate, increasing clinic capacity exponentially decreased heart attack and other deaths. At a high patient arrival rate, the percent of patients ignored and average wait time also decreased sharply as clinic capacity increased but only up to a capacity of 20 after which, there was no noticeable improvement.

Armstrong Hospital (Rural)

In the Armstrong hospital (rural), for the medium patient arrival rate, the average wait time and percent of patients turned away decreased exponentially and percent of patients treated increased exponentially as the clinic capacity increased. The most drastic improvement was when the clinic capacity was 20. There was no visible pattern in heart attack or other emergent deaths at the low or medium patient arrival rates as a function of clinic capacity.

Forbes Hospital (Suburban)

In the Forbes hospital, similar to the telehealth/teletriage model, for the middle and high patient arrival rate, as the clinic capacity increased, the percent of patients turned away decreased exponentially and percent of patients treated increased exponentially. For the low patient arrival rate, no patients were turned away, regardless of clinic capacity. Additionally, at a high patient arrival rate, increasing clinic capacity exponentially reduced the average wait time. Only a clinic capacity of 20 (for middle arrival rate) and 28 (for high arrival rate) produced a sharp improvement in these outcomes, after which the improvement was negligible (Figure 2).

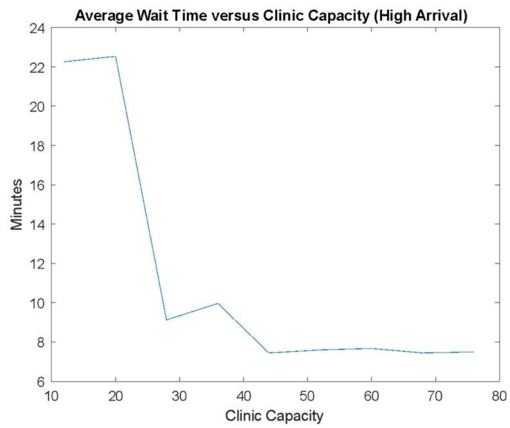


Figure 2A: Average wait time versus clinic capacity at the Forbes hospital (suburban) at a high arrival rate.

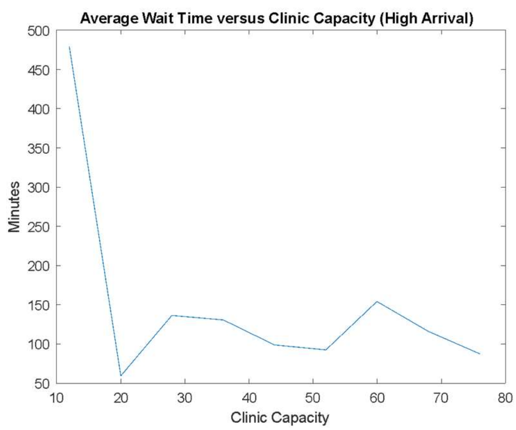


Figure 2B: Average wait time versus clinic capacity at the Armstrong hospital at a high arrival rate.

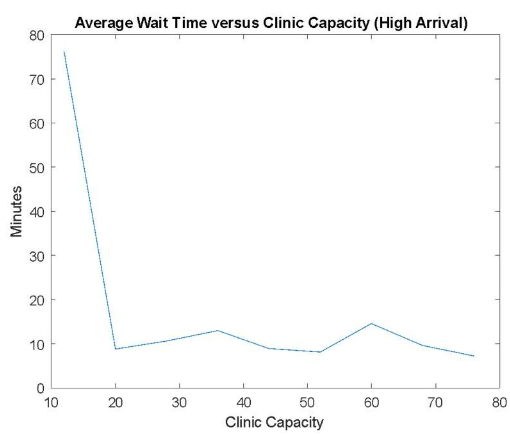


Figure 2C: Average wait time versus clinic capacity at the Allegheny hospital at a high arrival rate.

Surprisingly, for the medium patient arrival rate, increasing clinic capacity increased the number of heart attack deaths and other emergent deaths. However, this could have been due to high variation in the data from the low sample size. This reasoning is thought to be the case because this same pattern was not observed in the high patient arrival rate scenario. In the high patient arrival scenario, increasing clinic capacity produced a moderate decrease in the number of other emergent deaths, but there was no pattern in the number of heart attack deaths.

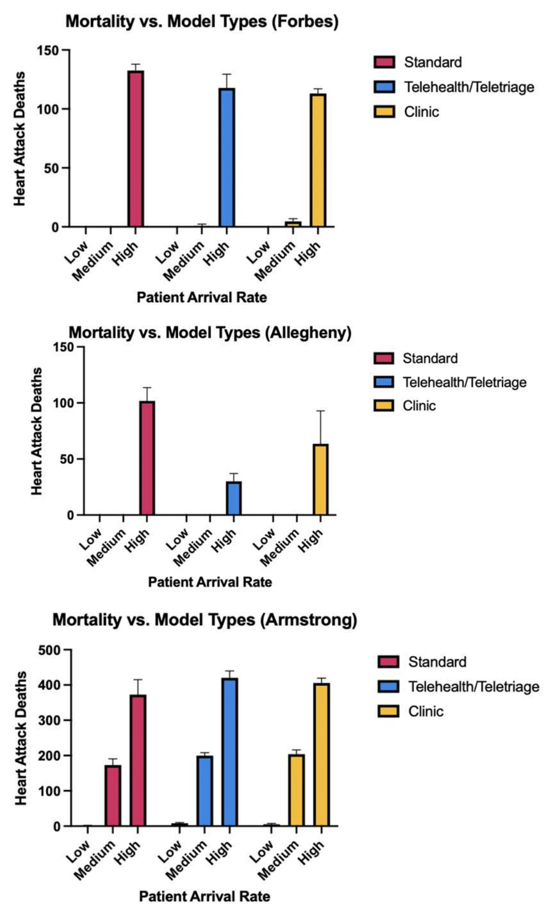


Figure 3: Bar plots comparing heart attack deaths across various patient arrival rates and hospital models

Discussion

The results show that the addition of teletriage, telehealth, or a co-located clinic all improve (decrease) heart attack mortality rates for hospitals located in urban and suburban areas. According to a multiple one-tailed t-tests statistical analysis (Figure 4), there was a significant difference in heart attack deaths with the addition of telehealth/teletriage and co-located primary clinic in the Allegheny and Forbes hospitals, or the urban and suburban areas. In the case of the Armstrong hospital, or rural area, there was no significance in heart attack deaths with the addition of the treatments in comparison to that of the baseline model.

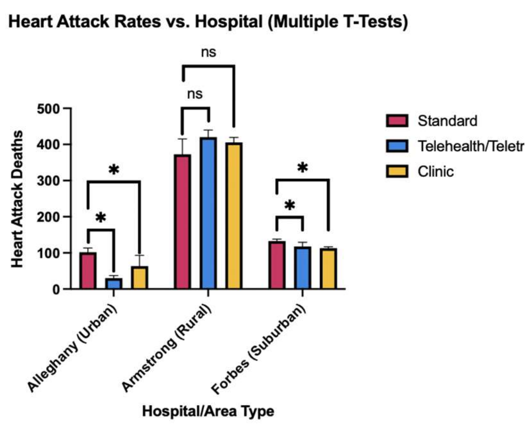


Fig. 4. Multiple one-tailed t-tests comparing heart attack mortality across hospitals and model types

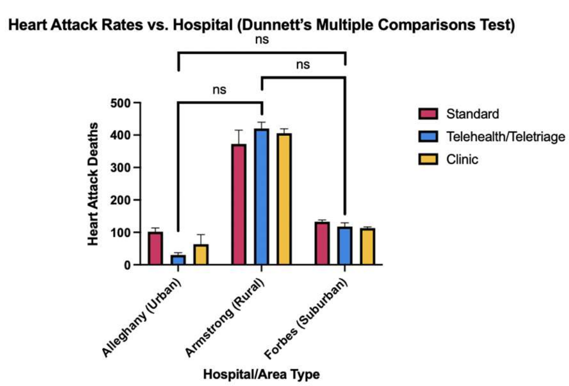


Figure 5: One-way ANOVA test comparing heart attack mortality across hospitals and model types

To verify and account for variance, an additional one-way ANOVA test was performed on the same dataset, comparing the improved models to the baseline across the different hospitals (Figure 5). However, there was a high adjusted p-value of 0.9943 and 0.9977 for baseline vs. telehealth/teletriage and baseline vs. clinic, respectively. This difference between tests could be attributed to the small sample size and the limitations mentioned later.

Additionally, both of these improvements lower the percent of patients turned away and increase the percent of patients treated. In urban and suburban hospitals, the addition of teletriage and telehealth to the hospital system has a greater impact on decreasing mortality rates when compared to the addition of a co-located primary clinic. Based on the flow of the agents (patients) through the hospital in the simulation, the hypothesized reason for this outcome is that teletriage and telehealth components alleviate patient crowing in the Emergency Department by redirecting non-emergent patients to receive virtual treatment only which in turn reduces potential crowding in the registration and triage areas. For future iterations of this project, it is recommended to find larger sample sizes and other hospital factors to test this hypothesis and to statistically verify this observation.

This model showed the most clear patterns and expected behaviors in the urban hospital (Allegheny) regarding the test variables: average wait time, percent of patients turned away from the Emergency

Department, percent of patients treated, number of non-heart attack deaths, number of heart attack deaths. As the hospital size decreased (to suburban Forbes and then rural Armstrong hospitals), the results became less conclusive. This indicates that either decreasing crowding in Emergency Departments results in more significant improvements in urban hospitals, or, the agent-based model is better suited for larger hospital systems as a result of the limitations of the input variables used in this specific model.

Limitations

In order to ensure that the model is representative of the real world,

First and foremost, the biggest limitation of this experimental design is the number of experiments run. Due to constraints, the experiments for each hospital and relative model type (baseline or either improved models) were run 4 times. A normal distribution was assumed for the dataset. Because of the low number of experimental trials, there could be changes in the results over patient arrival rates and especially with the improvements made to the models. The next limitation is the time values, which were only in multiples of 15, representative of 15 minutes. The values input into the model weren't exact to that of hospital data. Because of the limited hospital data made available as open source, for the values that weren't available, national averages had to be used, which may be different or not applicable to those of Pennsylvania hospital and specifically to the areas that were chosen. The patient arrival rates were all rounded to closest non-zero integers, which would have affected the accuracy and precision of the outcomes. Lastly, the code only considers patients arriving from the ER in the total hospital flow.

Regarding potential next steps to take in this research project, it is necessary to refine the agent-based model by contacting individual hospitals for more specific hospital-level data. As this project was only able to use free, open source data, when certain variables were not accessible for that limitation, national averages had to be used. Additionally, another step is to make more improvements to the model's algorithm to more accurately reflect hospital flow. Another step is to increase the sample size of runs to produce more conclusive results as well as increasing the sample size of hospitals that fall within the three geographical categories to conduct a larger breadth of statistical analysis.

To validate the three models used in this project after refinement, it would be beneficial to incorporate hospitals that have implemented at least one of the proposed improvements (teletriage/telehealth or a co-located clinic) and compare the outputs from the corresponding model with those charted by the hospital.

Materials and Methods

Previous Studies

Past studies use a simulation product, EDism model to test alternative scenarios for existing and proposed emergency departments to improve Key Performance Indicators (KPIs), including length of stay, bed utilization, and elimination of bottlenecks [10]. The research used simulation to identify methods to improve length of stay and availability of beds. This research studied Carondelet St. Mary's hospital in southern Arizona and built a model to study defined scenarios such as arrival volumes, inpatient beds, and process improvements [10]. The algorithm used introduces process improvements to find the best scenario combinations and solve for constraints by identifying arrival volume, hospital capacity at a fixed volume, testing the ratio of main ED beds to FastTrack beds and then testing the process improvements. For each simulation experiment, KPIs were tracked. Researchers then outlined a path of patients after arrival at the ED. Examples of process improvements made include bedside triage, eliminating non-value added activities, and moving inpatient discharge to earlier in the day. Additionally, sensitivity analysis was performed to identify significant impact on outcomes. Researching prior art allowed the team to gain inspiration for adaptations of this model and future research in this field [10].

Next steps to improve upon this model include contacting individual hospitals in order to obtain specific data that was unavailable as public, open source data. Additionally, making improvements to the model so that it more accurately reflects hospital flow such as using time values that are not constrained to multiples of 15 as well as using a slower patient arrival time minimum for rural hospitals. Another improvement is performing more runs and using a larger data set to increase the validity of the results.

Data Collection and Analysis

Open source hospital data sets on heart attack treatments were used from three hospitals in Pennsylvania. All of the open source data was found primarily through the American Hospital Directory as well as other sources. All of the data is hospital specific and provides averages of the hospital rather than specific to patients. This is beneficial as regulations around patient identifiers are not needed. The three hospitals that were used are Armstrong County Memorial Hospital in Kittanning, PA; Allegheny General Hospital in Pittsburgh, PA; and Forbes Hospital in Monroeville, PA. Armstrong County Memorial Hospital is located in a rural area of Pennsylvania, Allegheny General Hospital is located in an urban area, and Forbes Hospital is in a suburban area. This combination of hospitals was chosen to ensure an accurate representation of the state. The variables include percent of emergent patients, percent of non-emergent patients, percent of heart attack patients, percent of patients that need to be transferred, percent of patients that need emergency and ambulatory surgery, and percent of patients discharged who do not need hospital treatment [9]. A flow chart was created to visualize the patients' paths through the hospital as the basis of the algorithm. The algorithm was developed using Netlogo.

An agent-based model was developed using Netlogo that simulates hospital flow. A baseline code was developed using specific parameters for each hospital, or appropriate estimations in cases in which the data was not available, and a normal patient arrival rate. Improved hospital codes that included proposed alternatives to improve the system such as telehealth and teletriage were developed for each hospital as well. One improved model contains a co-located primary clinic where non-emergent patients are directed for treatment and the other model contains a combination of teletriage and telehealth treatment components. Teletriage allows non-emergent patients to be assessed for any need to be admitted to the hospital. If they do require hospital care, they can bypass hospital triage. Telehealth treatment also allows certain non-emergent patients to receive treatment virtually if the ER is full.

The baseline code was run for each hospital using Netlogo's BehaviorSpace feature and the final outputs were measured for each run. The baseline code (flow seen in Figure 6) was run again with the same parameters but at a high patient arrival rate as well as a larger percentage of non-emergent patients to represent a stress on the system. Outputs were measured for each run. Each of the improved hospital models were run for low and high patient arrival rates with outputs measured as well. In each experiment, a range of improvement capacities were selected for the proposed improvements with 30 runs for each capacity value. The models were run for the appropriate amount of time that were needed to simulate hospital flow for three months.

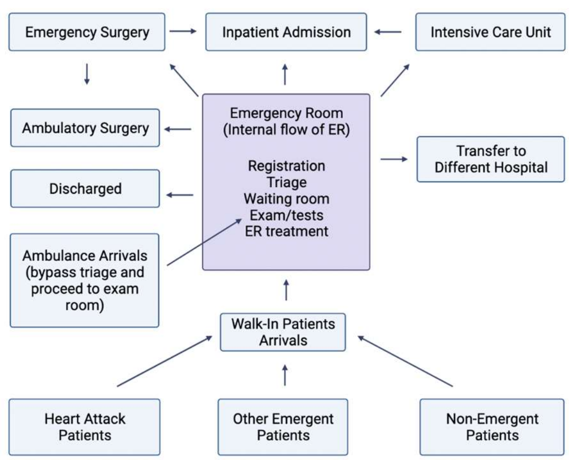


Figure 6: Flow chart of a baseline hospital as captured by the algorithm of the current code in Netlogo.

After each run, the average wait times, percent of patients turned away, percent of patients treated, number of heart attack deaths, and number of other deaths were measured. The percent of patients that are not included in computations, due to all components reaching maximum capacity, was also included. This variable also considers patients who are still in the process of being treated while the simulation is paused. The average final outputs were then graphed as a function of ticks (time) in order to visualize emerging behavior. The graphs also help to identify a point of diminishing returns at which hospital flow cannot be improved by increasing the improvement size.

Explanation of Code Development

For every tick, all patients, including walk-in and ambulance, are created and added at the bottom of the simulation (Figure 7 depicts snapshots of all three model interfaces). In this code, ambulance patients are either heart-attack or other emergent patients and they are sent straight to the exam room. Walk-in patients include heart-attack, other emergent, and non-emergent patients. Patients are sent to the blue box to wait for registration. If there is space in the red box, patients are then sent there to be registered and triaged. Patients must wait a certain amount of ticks in the red box, which represents registration time. After registration and triage, heart-attack patients and other emergent patients are first moved to the exam room (magenta box) until it is full. Remaining non-emergent patients are then moved to the exam room until it is full. If the exam room is full, heart-attack patients and other emergent patients are moved first to the waiting room (violet box) and then, the remaining non-emergent patients are moved to the waiting room. As spots become open in the exam room, patients are shifted from the waiting room to the exam room in order of urgency and arrival. Patients that are in the exam room must wait for a certain number of ticks as a representation of testing time.

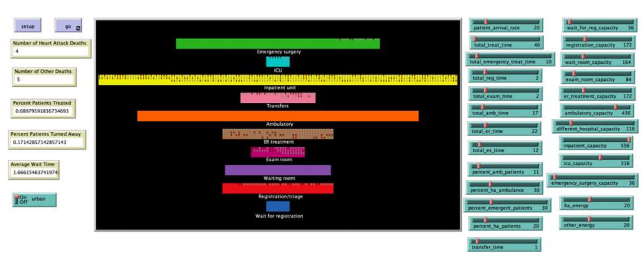


Figure 7A: Snapshot of agent-based simulation of standard hospital. The left column with beige outlined boxes shows an overview of the simulation run data. The middle box in black represents the hospital flow with the colored boxes being different parts of the hospital. The agents (patients) move within the boxes dependent on where they are in their treatment timeline. The right are various data points for the hospital that the specific simulation is representing.

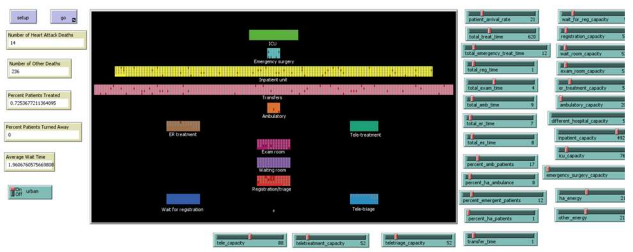


Figure 7B: Snapshot of agent-based simulation of hospital with teletriage (represented by sky-colored box) and telehealth (represeted by turquoise box).

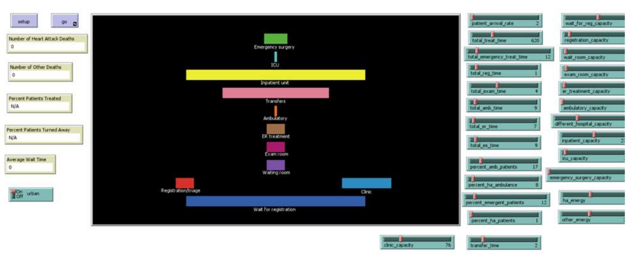


Figure 7C: Snapshot of agent-based simulation of hospital with co-located primary clinic added (represented by sky-colored box).

Once examination is complete, patient paths diverge. Each spawned patient has a specific path variable that determines what type of treatment is needed in the hospital. The variables for heart-attack patients are:

- "Er-to-inpatient"
- "Icu-to-inpatient"
- "Es-to-inpatient"
- "Different-hospital".

For other emergent patients, the variables are:

- "Er-to-inpatient"
- "Icu-to-inpatient"
- "Es-to-inpatient"
- "Different-hospital".

For non-emergent patients, the variables are:

- "Er"
- "Ambulatory"
- "Discharge"

"Er-to-inpatient" means that after completing testing, the patient moves to ER treatment (brown box) for emergency treatment if spots are available. Once emergency treatment is complete, they are moved to the inpatient unit (yellow box) for emergency and regular treatment. If emergency treatment in the ER is complete but the inpatient unit is full, they continue their recovery in the ER until the inpatient unit has space. "Icu-to-inpatient" means that after completing testing in the exam room, the patient moves to the ICU (green box) for emergency treatment if spots are available. Once emergency treatment is complete, the patient is moved to the inpatient unit for the rest of treatment. If the ICU is full, the patient is directly transferred to the inpatient unit for emergency and regular treatment. If emergency treatment in the ICU is complete but the inpatient unit is full, the patient continues their recovery in the ICU until the inpatient until opens up. For "es-to-inpatient", after completing testing in the exam room, the patient moves to the emergency surgery box (cyan box) for emergency surgery if spots are available. If this box is full, the patient is moved to the ambulatory surgery box (orange box). In either box, the patient will stay for a certain number of ticks to represent the completion of emergency surgery, and then they are transferred to the inpatient unit for recovery. If the inpatient unit is full, the patient continues recovery where they are until spots become available. For "different-hospital", after completion of testing in the exam room, if a different hospital is available (urban switch is on) and the hospital is full, emergent patients are transferred to the pink box to represent the transfer. For simplicity, all transfer patients complete emergency treatment and stable treatment in the pink box until discharge. Additionally, other patients designated for transfer will be transferred to the pink box after testing. For "er", after completing testing in the exam room and transferring emergent patients to their appropriate locations, non-emergent patients will be transferred to the ER for treatment. If the ER is full, their path is changed to "discharge" and they will be turned away.

For "ambulatory", after completing testing in the exam room, non-emergent patients are transferred to the ambulatory surgery box if spots are available where they will spend a certain number of ticks being treated until discharge. For "discharge", some patients will be automatically designated for discharge, which means that they do not need treatment. Patients that have been successfully treated will have their paths changed to "discharge" to signal the model to remove them from the simulation.

The model then updates the energy of emergent patients. Emergent patients who have not finished emergency treatment will have their energy decrease by 1 for each tick that passes. If their energy reaches 0, they die. The model updates the average wait time of all patients as well. The code then deletes all patients that have been designated for discharge or have an energy <=0 and removes them from the simulation.

In the improved models, for the telehealth and teletriage simulation, non-emergent patients are triaged online in the sky-colored box if spots are available instead of going to the blue box for registration. If the patients' paths are "er" or "ambulatory", they must go to the hospital where they will be sent directly to the exam room if spots are available or to the waiting room with no hospital triage needed. If the ER is full, patients with "er" pathways will not be turned away and will be sent to the telehealth box (turquoise). Treatment time in telehealth is the same as treatment time for non-emergent patients in the ER. For the primary clinic code, after completing registration and triage in the red box, all non-emergent patients except for ambulatory patients are sent to the clinic (turquoise box) for examination and treatment so they do not need to go to the hospital and are discharged. Treatment time in the clinic is the sum of examination time and treatment time for non-emergent patients in the ER.

Telehealth Code Assumptions

- Telehealth treatment time is the same as ER treatment time

Co-located Primary Clinic Code Assumptions

- After triage, all non-emergent patients are transferred to the clinic if spots are available.
- Treatment time in the clinic is the sum of exam time and ER time that non-emergent patients would have spent in the hospital.

Data Processing

General parameters that could not be obtained for specific hospitals were determined by collecting national data through the CDC as well as other sources. The percent of total emergent patients among ED arrivals was determined to be 13%, found by summing the percent of patients in the upper two triage levels (Immediate and Emergent) in the National Ambulatory Medical Care Survey (2018). The percent of ED patients with acute myocardial infarction, 0.2%, was determined by dividing the number of patients with this condition by total number of ED visits in this survey. The percent of patients needing to be discharged without treatment (1%), transferred to a different hospital (2.3%), transferred to the operating room for emergency/ambulatory surgery (1%), or were ambulance patients (17%) were also determined by dividing the number of patients in the corresponding categories by the total number of ED visits. The percent of admitted patients being sent to the Intensive Care Unit, 14%, was also available through the CDC [11]. The treatment time in the Emergency Room, 110 minutes, for non-emergent patients was determined by taking the weighted average of treatment time for each of the three non-emergent triage categories (urgent, semi-urgent, and non-urgent) based on the percent of patients in each of those categories, found in the 2010-11 National Ambulatory Medical Care Survey. Similarly, treatment time in the ER (177 minutes) for emergent patients was determined by taking the weighted average of treatment times in each of the two emergent triage categories [12]. Average time for emergency/ambulatory surgery was found to be 135 minutes and average time for recovery/additional treatment in the inpatient unit was found to be about 6.5 days (between 3 and 10 days) [13] [14]. The time limit for survival of both heart attack patients (and other emergent patients as well due to lack of data) was estimated to be about 70 minutes [15]. Registration time was estimated to be about 15 minutes, and exam time was estimated to be about 1 hour [16]. Due to limitations in obtaining ED capacity data, it was estimated that for any given hospital, ER bed capacity, exam room capacity, waiting room capacity, and registration/triage capacity would be 10% of the inpatient capacity.

Specific data for individual Pennsylvania hospitals (Allegheny General Hospital, Forbes Hospital, and Armstrong County Memorial Hospital) was found by analyzing hospital reports available from the Pennsylvania Department of Health. Patient arrival rate (per 15 minutes) to a specific hospital was determined by dividing the total number of ED visits to that hospital by the number of 15 minute increments in a year (35,040). Additionally, the number of inpatient beds, ICU beds, and operating rooms (which were assumed to be equally divided between emergency and ambulatory surgeries) in each hospital was available in the reports. It was found that Allegheny had 498 inpatient beds, 74 ICU beds, and 39 operating rooms; Armstrong had 135 inpatient beds, and 6 operating rooms; and Forbes had 277 inpatient beds, 38 ICU beds, and 13 operating rooms. The time to transfer patients to a different hospital was determined by finding the average driving time to all the nearest hospitals (<30 minutes away) to a given hospital. The transfer capacity, or maximum amount of patients that can be transferred, was determined by multiplying (1 - occupancy rate) by inpatient capacity of each nearby hospital and calculating the sum. Allegheny had a transfer time of about 10 minutes and a transfer capacity of 576 beds; Armstrong had a transfer time of 21 minutes and a transfer capacity of 25 beds; Forbes had a transfer time of 26 minutes and a transfer capacity of 169 beds [17].

After data values were obtained, certain adjustments needed to be made to input the parameters for each hospital within the Netlogo sliders. This included rounding all time values to the nearest multiple of 15, rounding percent values and patient arrival rates to the nearest non-zero integer, and rounding bed capacities to the nearest multiple of 8 and then adding 4. It should be noted that the distribution of percent patients allocated to certain treatment paths (such as percent patients admitted to the ICU) had to be coded into Netlogo as there were no sliders in the interface for these variables.

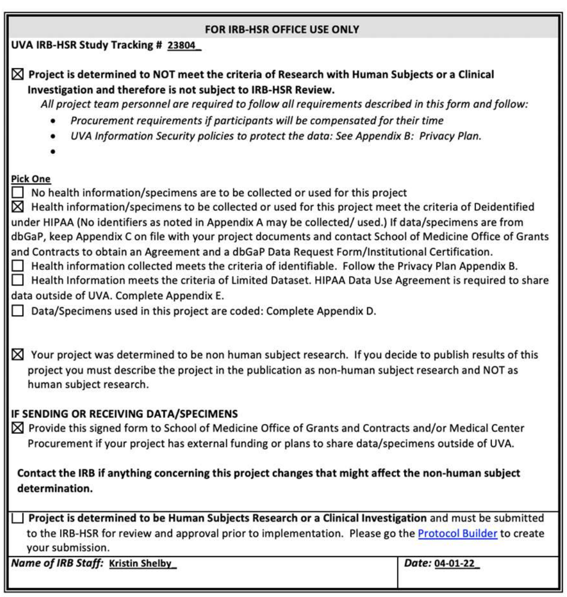
Appendix

Additional Analysis Figures

For all figures and data collected when running experiments on the agent based model, see the supplemental documents.

Proof of IRB Exemption

For this project, we were in contact with the University of Virginia's Institutional Review Board for Health Sciences Research (IRB-HSR) office. Upon sharing with them our project methods and data sources, they deemed our project "non human subject research." As such, we did not need to obtain an IRB-HSR review (Figure 8).



FOR IRB-HSR OFFICE USE ONLY

UVA IRB-HSR Study Tracking # 23804

☒ **Project is determined to NOT meet the criteria of Research with Human Subjects or a Clinical Investigation and therefore is not subject to IRB-HSR Review.**

All project team personnel are required to follow all requirements described in this form and follow:

- *Procurement requirements if participants will be compensated for their time*
- *UVA Information Security policies to protect the data: See Appendix B: Privacy Plan.*
-

Pick One

☐ No health information/specimens are to be collected or used for this project

☒ Health information/specimens to be collected or used for this project meet the criteria of Deidentified under HIPAA (No identifiers as noted in Appendix A may be collected/ used.) If data/specimens are from dbGaP, keep Appendix C on file with your project documents and contact School of Medicine Office of Grants and Contracts to obtain an Agreement and a dbGaP Data Request Form/Institutional Certification.

☐ Health information collected meets the criteria of identifiable. Follow the Privacy Plan Appendix B.

☐ Health Information meets the criteria of Limited Dataset. HIPAA Data Use Agreement is required to share data outside of UVA. Complete Appendix E.

☐ Data/Specimens used in this project are coded: Complete Appendix D.

☒ Your project was determined to be non human subject research. If you decide to publish results of this project you must describe the project in the publication as non-human subject research and NOT as human subject research.

IF SENDING OR RECEIVING DATA/SPECIMENS

☒ Provide this signed form to School of Medicine Office of Grants and Contracts and/or Medical Center Procurement if your project has external funding or plans to share data/specimens outside of UVA.

Contact the IRB if anything concerning this project changes that might affect the non-human subject determination.

☐ **Project is determined to be Human Subjects Research or a Clinical Investigation** and must be submitted to the IRB-HSR for review and approval prior to implementation. Please go the Protocol Builder to create your submission.

Name of IRB Staff: Kristin Shelby	*Date:* 04-01-22

Figure 8: University of Virginia's Institutional Review Board (IRB) office exemption from requiring an IRB-HSR review.

Hopital Flow Model Assumption List

- It is assumed that patient arrival rate is constant throughout the day, which may not be the case in real life.
- Patients are grouped into one of only three categories: heart-attack, other emergent, and non-emergent.
  - This does not take into account more specific types of diseases or triage categories.
- There are only a few possible treatments paths: "er" for non-emergent patients being treated only in the ER, "er-to-inpatient" for emergent patients who receive emergency treatment in the ER and are then moved to inpatient, "icu-to-inpatient" for emergent patients who need care in ICU and then are moved to inpatient unit to finish treatment, "es-to-inpatient" for patients who receive emergency surgery and then are moved to inpatient for recover, "ambulatory" for non-emergent patients who need ambulatory surgery, and "different-hospital" for all patients designated to be transferred to a different hospital. In reality, there are additional pathways that patients may take in the hospital.
- There are no specialized hospital components. For example, the ICU box (green box) takes all patients who need the ICU. However, many hospitals have specific critical care units, such as a cardiac care unit. This is likewise for the inpatient unit; there are no specialized components.
- All walk-in patients have the same registration and triage time.
- All non-emergency treatment, or recovery time, after an emergent

patient is stabilized takes the same amount of time.

- Ambulatory surgeries are strictly non-emergent surgeries.
- Non-emergent patients do not need to be admitted to the inpatient unit: they can either be treated in the ER room, need ambulatory surgery, or be discharged.
- The order of arrival in the exam room: emergent patients in the waiting room are moved first, then emergent patients who finished triage, then non-emergent patients in the waiting room, then non-emergent patients who finished triage.
- Wait time is the sum of time spent waiting for registration, completing registration, and sitting in the waiting room.
- If the urban switch is off, patients designated for transfer to a different hospital are turned away from the exam room.
- Patients who need critical treatment but don't have "er" in their path variable will not be moved to the ER for treatment even if other hospital components are full.
- If the ICU is full, patients go straight to the inpatient unit for emergency and stable treatment.
- If emergency surgery is full, patients go to the ambulatory surgery room.
- Patients only get transferred to a different hospital if the urban switch is on.
- Patients receiving emergency treatment in the ICU and ER take the same amount of time.
- IF ICU, emergency surgery, and ER patients do not find a spot in inpatient to finish treatment, they finish treatment where they are until inpatient beds open up.
- If the urban switch is on, and all hospital components are full, emergent patients automatically get transferred to a different hospital if spots are available.
- Assigned a uniform emergency and regular treatment time for all emergent patients transferred to different hospitals, regardless of their specific path variables.
- The code assumes that all heart-attack patients have the same time limit for survival.
- The code assumes that all other emergent patients have the same time limit for survival.
- Patients who are admitted to the ICU or emergency surgery don't spend time in the ER treatment room, but in reality they may spend some time being resuscitated.
- Emergent patients are only out of their critical state once they complete emergency treatment. After that, their energy variable will not decrement further.
- If a different hospital is available, all patients transferred will get the appropriate care that they need, for example, an emergency surgery patient will be able to get emergency surgery.
- Assumed that ER capacity was about 10% of inpatient capacity.
- Distribution of illnesses (heart attack, emergent, and non-emergent) are the same even when patient arrival rate increases after a regional disaster. However, in reality, this may not be the case and there could be a greater percent of non-emergent patients arriving during the pandemic.

List of Limitations

- Time values can only be in multiples of 15 (since each tick represents 15 minutes).
- Patient arrival rate must be rounded to the closest non-zero integer.
- Code only considers patients arriving from the ER in the total hospital flow.
- Lowest patient arrival rate possible is 1 (1 patient per 15 minutes), which makes it difficult to accommodate extremely small rural hospitals.
- Unknown ED capacities, which have a significant impact on outputs.
- Specific hospital data was very limited and as a result, national averages had to be used.
- Sample size of run at each set of parameters was very small (only 4) due to time constraints to run simulations.

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