Engineering a Resilient Regional Healthcare System: Improving Stroke Care in Shelby County, TN

A Technical Report submitted to the Department of Biomedical Engineering

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

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Spring, 2022

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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, The MITRE Corporation

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Abstract

Strokes are a leading cause of death in the United States, and healthcare systems often fail to deliver the timely care that is critical for stroke patients. Additionally, healthcare systems are designed in a suboptimal manner, mainly focusing on fixed facilities that may not be resilient in high-strain scenarios, while many other healthcare resources go underutilized or overlooked. By reallocating healthcare resources, healthcare systems would be able to provide better stroke care in times of high-strain. This work focuses on a regional healthcare system, specifically that of Shelby County, Tennessee. By using agent-based modeling (ABM) in NetLogo, Shelby County's healthcare system as well as patient-provider interactions were modeled. The model was then altered to discover ways that the healthcare system could be improved through reallocating healthcare resources by changing healthcare facility locations, provider capacities, and adding more healthcare providers. Stroke death rate increased as a result of limiting the distance patients were able to travel, demonstrating how patient health is tied to healthcare access; implementing telemedicine could complement preventative measures in this scenario. Stroke prevalence also increased as a result of decreasing provider capacities. This demonstrated the need for more alternative providers such as advanced practice providers (APPs) that could address provider shortages at the preventative level. By adding new providers in areas lacking them, it was revealed that overcrowding of existing providers could be reduced while simultaneously treating more patients. This further demonstrates the need for providers in areas that currently lack adequate healthcare infrastructure.

Keywords: Simulation; Healthcare; Resilience; Stroke; Agent-Based Modeling; Netlogo

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Introduction

Most current healthcare delivery models focus on fixed care facilities, while leaving many other resources under or ineffectively utilized[1]. This approach to healthcare system design limits flexibility, especially in high-strain scenarios such as natural disasters or a pandemic, since these systems lack resilience and adaptability. As has been seen with the Covid-19 pandemic, these healthcare systems were not well-equipped with the right resources or enough personnel to address the healthcare of all individuals in a population. This is evident given that the mortality rate for Covid-19 among Black Americans was 2.6 times higher than that of White Americans[2]. Additionally, 33% of hospitalized patients were Black compared with 45% who were White, even though these groups make up 13% and 76% of the United States population, respectively[2]. These statistics exemplify the disproportionate effects of Covid-19 on racial and minority groups that can be explained by factors such as low socioeconomic status, lack of health insurance, or poor living conditions. To provide better healthcare coverage to these more vulnerable groups particularly in the midst of a public health emergency, this requires change to the present healthcare system model including enhanced resilience through reallocating healthcare resources.

When under strain, healthcare facilities experience congestion and delays in providing quality care to all patients, while other regional resources remain unused. These bottlenecks are often most detrimental to those people who already lack access to sustainable healthcare. For example, a cross-sectional survey of Latino parents found that language problems, cultural differences, poverty, transportation difficulties, long wait times, and a lack of health insurance are the major access barriers to Latino children's health[3]. Latinos will soon be the largest minority group in the United States, yet they face many barriers to healthcare that would only be exacerbated by a high-strain scenario. These barriers are particularly prominent for the care of chronic and common diseases, such as cardiovascular diseases.

Disease Focus: Stroke

One cardiovascular disease that is greatly affected by insufficient healthcare delivery is strokes. Stroke care is a critical area of healthcare delivery to address considering someone in the United States has a stroke every forty seconds, and that strokes are a leading cause of death[4]. Time is a crucial factor for stroke survival, with tissue necrosis beginning just minutes after symptom onset; however, only one in four patients arrives at a hospital within the optimal timeframe for critical treatments to be administered[5]. Not only is the time to hospital critical and often lacking, so is the time to treatment upon patient arrival. Preventative interventions are also imperative to reducing stroke incidence and mortality. With all of these significant factors, it is often the case that a healthcare system is not excelling at its healthcare delivery to all patients. Therefore, this work focuses critically on stroke care when analyzing current gaps in a regional healthcare system.

Regional Healthcare System: Shelby County, Tennessee

This work also focuses on a specific regional healthcare system to ensure accurate analysis and modeling of healthcare resources for that region. The chosen region is Shelby County, TN, which was selected for a multitude of reasons. Firstly, this county was selected for its size, meaning it possesses a wide variety, and a large enough quantity, of healthcare resources to allow for effective data analysis and optimization[6]. Secondly, Shelby County was selected for its high prevalence of strokes. A vascular neurologist from the county said that "If you live in Shelby County you have a 30 percent higher risk of having a stroke compared to the rest of the country"[7]. This increased prevalence is due to the county population's overall poor diet and lack of resources, as well as the underlying health factors that the many African Americans in Shelby County face[8]. Due to these aspects, the healthcare model was created for stroke care in Shelby County, TN and leverages the regional healthcare resources and economics present there.

Agent-Based Modeling

The overarching goal of this work is to engineer a more resilient regional healthcare system through reallocating resources for stroke care in Shelby County, TN. To accomplish this goal, a data-driven model of the county's healthcare system was created using agent-based modeling (ABM). ABM is a type of simulation modeling that examines the micro-level interactions between agents, both human and nonhuman, within a system[9]. Examples of agents in a healthcare system include clinicians and social workers, along with treatment facilities. Given the versatility of ABM to provide a comprehensive view of healthcare systems, this is the modeling approach utilized to create a model of Shelby County's healthcare system.

Resilience

A major component of simulation models are the resilience metrics used to evaluate system effectiveness during high strain scenarios. Resilience is a term used in systems engineering to refer to the ability of a system to return to an original state after experiencing deformation[10]. For a healthcare system, this involves being able to provide adequate healthcare shortly after a time of suboptimal healthcare delivery. Relevant resilience metrics include duration to failure, duration to recovery, and performance before and after recovery[11]. This work incorporates resilience through a discussion of recommendations and changes that could be made to Shelby County's healthcare system to increase its resilience during high-strain scenarios.

Innovation

Similar research has been carried out to optimize resource usage or implement resilience for various disease areas and geographical locations. A variety of operations research (OR) and optimization techniques are typically used to carry out resource allocation and healthcare system optimization problems; however, the effectiveness of OR modeling is limited by a lack of representative or quality data, and a lack of implementation of the models. The four main areas that OR has been applied to in relation to global health are clinical medicine, public health, health innovation, and health systems and operations[12].

A specific study examined the priority and allocation of healthcare resources in developing countries, with a focus on a specific region in Tanzania. Although this study is similar to the work presented here overall, the objectives considered most important are different from the priorities of this work and there is not a focus on a specific disease area. The location of the study is also vastly different and will result in an incomparable analysis of the current resources available[13]. Another study focuses on Type 2 diabetes and the optimal allocation of resources available for four different interventions. An optimization model was created to identify trade-offs within the continuum of care for diabetes[14]. Again, the goal of the research is in line with that of this work, even though it focuses on a different disease; however, there is no geographical focus to result in a regional healthcare system analysis. The study does not incorporate resilience either.

It is important to note that there has been much research into healthcare system resilience strategies with different approaches including the improvement of responses to patient volume surges, design improvements to a variety of devices/equipment, and the maintenance of enough medical personnel[15]. The work presented here is significant in that it incorporates a specific disease area and geographical region, while considering resource allocation and resilience. By doing so, the finished model provides a unique approach to healthcare system resource allocation that will give Shelby County's healthcare system the ability to be resilient and provide improved care to stroke patients no matter the situation.

Aims

The first aim of this work was to assess current gaps in a regional healthcare system's ability to treat stroke patients. This entailed gathering data about various resources available within Shelby County's current healthcare system. The second aim of this work was to build a data-driven model to represent the healthcare system of Shelby County. This was accomplished through the implementation and validation of an ABM model in NetLogo that simulated stroke care through patient-provider interactions and patient movement throughout Shelby County. The last aim of this work was to incorporate resilience into the healthcare system for high-strain scenarios. This entailed drawing conclusions and making recommendations regarding resilience from the experiments ran with the ABM model.

Materials and Methods

Assessing Current Gaps in the Healthcare System of Shelby County

The first aim of assessing gaps in Shelby County's healthcare system was accomplished by gathering data on healthcare resources available in the county. Data was collected by the 36 ZIP Code Tabulation Areas (ZCTAs) that make up Shelby County. Datasets were found for population, stroke prevalence and death rate, ICU bed capacity, as well as Medicare provider data[16–20]. Considering that strokes are predominantly more common in adults over 18, all those under 18 years of age were excluded from the total adult population used for the model[21]. The provider data included those providers at the preventative, operative, and rehabilitative levels of stroke care. The providers were categorized into one of these three categories based on each provider's role in the continuum of care for stroke patients (Table 1). This work uses mutually exclusive categorizations of the providers, even though in reality a single provider may provide care in more than one of these categories.

Table 1: Preventative, operative, and rehabilitative provider types

Preventative	Operative	Rehabilitative
Family Practice	Ambulance Service Provider	Cardiology
General Practice	Ambulatory Surgical Center	Cardiologist
Geriatric Medicine	Cardiac Surgery	Clinical Laboratory
Internal Medicine	Certified Registered Nurse Anesthetist (CRNA)	Hematology
Nurse Practitioner	Critical Care (Intensive)	Licensed Clinical Social Worker
Physician Assistant	Diagnostic Radiology	Neurology
Registered Dietitian or Nutrition Professional	Emergency Medicine	Occupational Therapist in Private Practice
Undefined Physician Type	General Surgery	Pharmacy
	Interventional Radiology	Physical Medicine and Rehabilitation
	Neurosurgery	Physical Therapist in Private Practice
		Speech Language Pathologist

Geographic Information System

To create a spatial representation of Shelby County, a geographic information system (GIS) was utilized. ZCTA Census data from 2020 was implemented into ArcGIS software and the ZCTAs within Shelby County were selected and data on stroke prevalence, population, and facilities was associated with the ZCTAs. The representation was then exported as a shapefile for implementation into NetLogo.

Design of the ABM Model

ABM is a computational approach that provides simulations of agents in a controlled environment. The environment of NetLogo is made up of a grid of squares, known as patches. The environment for this model depicted the geographic space of Shelby County, TN and its associated ZCTAs through the use of GIS. To incorporate time, one tick in NetLogo was assumed to be one day. The model was always run for 365 ticks to represent one year passing.

One agent of each provider type (preventative, operative, rehabilitative) was spawned in a random location throughout each ZCTA each time the model was set up. If a given ZCTA did not have any of a certain provider type, the agent representing that provider type was removed. The one preventative, operative, or rehabilitative provider agent in each ZCTA represented all of the preventative, operative, or rehabilitative providers that actually practice within that ZCTA. The number of providers per ZCTA was obtained from Medicare data. The number of patients that could be seen in a given day was calculated based on the total number of providers of each category in a given ZCTA. For one tick, the capacity a provider had was determined using the average number of patients seen by a provider in a day[22–33]. The reciprocal of the sum of averages for each provider type was then used to calculate the number of providers necessary to see one patient. These values for each provider type of each ZCTA were then summed, and using matrix multiplication with the previous reciprocals provided capacities for each ZCTA. The provider agents remained in the same location for the duration of each run of the model.

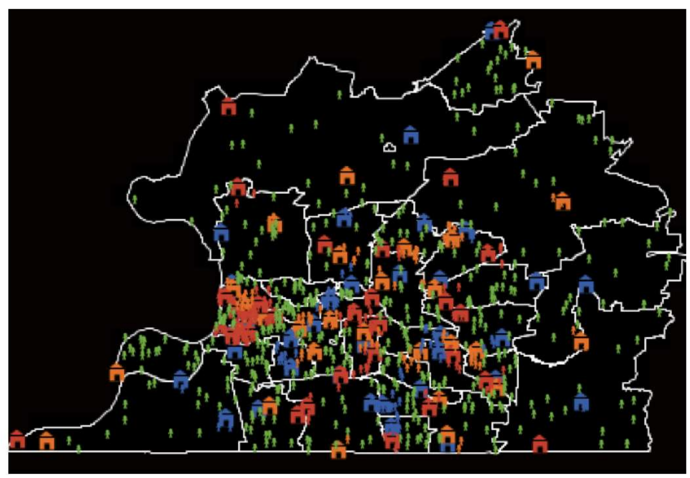

Fig. 1. NetLogo Model Interface with Patients and Providers. Each house-shaped agent represents a provider of a given type (blue – preventative, orange – operative, red – rehabilitative). Each person-shaped agent represents 100 people in Shelby County. The patients move within the border of Shelby County and interact with different providers within defined constraints. These interactions result in adjustments to patient health, which affects the patient's risk of stroke.

The population of Shelby County was scaled down by a factor of 100 to enable the representation of the necessary number of agents in NetLogo, reduce the runtime of each simulation, and provide an easier qualitative measure of patient interactions. The number of patients needed to accurately represent the population of Shelby County per ZCTA was spawned randomly throughout its corresponding ZCTA each time the model was run (Figure 1). Each patient in the population was then assigned a random health value ranging from 0 to 100 and sampled from a normal distribution with a mean of 50 and a standard deviation of 15. The patients were also assigned a stroke risk adjustment factor variable that corresponded to how much higher or lower the stroke prevalence of that patient's ZCTA was than the average stroke prevalence of the county as a whole. By including this adjustment factor, the variation in stroke prevalence from ZCTA to ZCTA is taken into account when calculating a patient's stroke risk.

The patients were allowed to move around the interface according to various rules. If a patient had a stroke, they remained at an operative provider's location for a duration of seven days. If a patient had not interacted with a provider, they moved toward any providers that were within a one patch radius of their current location. If no providers were within that range, the patients moved randomly. If a patient had interacted with a preventative or operative provider, the patient was not allowed to interact with another provider for a duration of ninety days. In all other cases the patients randomly moved within Shelby County; however, some patients would move outside the county border due to the pixel nature of NetLogo's interface. Since each pixel is a square, part of one square may be both inside and outside the border of Shelby County. In this case the patient was allowed to move to all areas of this square.

If a patient was on the same patch as a provider, the patient could interact with that provider within certain constraints. A patient could only interact with one provider each day and each provider could only interact with patients until its capacity was reached for the day. Patients could interact with preventative providers in all cases except when the patient had just interacted with either a preventative or an operative provider. Patients could interact with operative providers as long as the patient's health was less than or equal to 75. Patients could interact with rehabilitative providers if the patient had previously had a stroke, interacted with an operative provider, and had a health value greater than 50.

As a result of interacting with any of the provider types, patients experienced an adjustment to their health. This adjustment was calculated in two steps. First, a percent change was calculated according to the following equation, where x is the value to be subtracted as determined by which of the three provider types the patient interacted with. For preventative providers, x = 15, and for operative and rehabilitative providers, x = 10.

$$\% \text{ change} = 100 - \text{Health} - x \qquad [1]$$

If the percent change would be less than zero, it was increased to zero. Once the percent change was calculated, patient health was adjusted according to the following equation:

$$\text{Health} = \text{Health} * (1 + \% \text{ change}) \qquad [2]$$

If the health would be greater than 100, it was decreased to 100. Additionally, every patient's health decreased by a value of 3.75 every three months to account for a gradual decline in health over time. Any patient with a health value less than 0.25 died and was removed from the model.

At the end of each tick, a patient's stroke risk was calculated based on which of six health brackets the patient's health fell within. The six brackets were the following: health less than 25, health between 25 and 40, health between 40 and 55, health between 55 and 70, health between 70 and 85, and health greater than 85. Each of these health brackets was associated with its own stroke risk. This stroke risk was calculated using the American College of Cardiology (ACC) and the American Heart Association (AHA) heart risk calculator[34]. Values input into this calculator include: age, gender, race, total cholesterol, high-density lipoprotein (HDL) cholesterol, systolic and diastolic blood pressure, whether the patient was treated for high blood pressure, whether the patient has diabetes, and whether the patient is a smoker. For all the health ranges calculated, the patients were non-African American males aged 50 who were not treated for high blood pressure, did not have diabetes, and did not smoke. The cholesterol and blood pressure inputs were varied based on normal and unhealthy values to reflect patients of varying cardiovascular health (Table 2).

Whether or not a patient had a stroke was based on the patient's total risk. The total risk was the sum of the calculated risk value and the adjustment factor calculated from the patient's ZCTA's stroke prevalence. If a random number between 0 and 100 was less than the total risk, the patient was determined to have had a stroke. After having a stroke, the patient's health decreased by twenty.

Table 2: Parameters for the American College of Cardiology (ACC) and the American Heart Association (AHA) heart risk calculator

Health	Risk over 10 years (%)	Daily risk (%)	Systolic Blood pressure	Diastolic Blood Pressure	Total Cholesterol	HDL Cholesterol
Health ≤ 25	25.3	0.0069315	185	110	280	20
25 < Health ≤ 40	20.2	0.0055343	170	110	260	20
40 < Health ≤ 55	16.3	0.0044656	170	100	260	25
55 < Health ≤ 70	10.5	0.0028767	150	95	250	30
70 < Health ≤ 85	5.6	0.0015343	130	85	235	40
85 < Health ≤ 100	3.4	0.0009315	110	70	215	50

Model Validation

Validation metrics were evaluated to determine if the proposed ABM model was representative of Shelby County, TN. The average stroke prevalence of the county was obtained from 2019 data for each ZCTA and was calculated to be 4.56%. The average stroke death rate from 2017-2019 of Shelby County was 0.098%[35]. The proposed ABM model was run ten times, and the average stroke prevalence and death rate were recorded.

Experimental Methods

To obtain data for each run of the model, code was added to write data to .csv files. Additionally, the number of patients in each health bracket was manually recorded at tick 0, 90, 180, 270, and 365. The model was always run for 365 ticks to mimic the timespan of a year, with each tick representing one day. The model was run five times without any changes to obtain the necessary control data.

For the first experiment, the distance able to be traveled radially from each patient's point of origin within Shelby County was restricted. Three different distance limits were tested: 3, 5, and 7 patches. Five trials were run for each distance limit. In the model, 1 patch corresponded to approximately 1.03 miles east to west and 0.88 miles north to south.

For the second experiment, scaling factors were applied to the model to simulate provider capacity at 110%, 68.24%, 68.24% for operative providers only, and 50%. Besides the third condition that only adjusted operative provider capacity, each factor adjusted capacities for all three types of providers. 68.24% was the average ICU bed capacity for Shelby County in 2020-2021 and was incorporated to mimic the pandemic, a high-strain scenario. Five trials were run for each condition[36].

For the third experiment, operative and rehabilitative providers were added to the ZCTAs lacking them. Every ZCTA had a preventative provider, however 6 were lacking an operative provider and 6 were lacking a rehabilitative provider. Each provider added was given a capacity value based on the average capacity of the operative and rehabilitative providers. For operative providers the average capacity was 41.48 and for rehabilitative providers it was 33.69. Five trials were run for this experiment.

For the subsequent statistical analysis of the experimental data, the alpha value utilized was 0.05. For the datasets where data was collected at each tick, yielding 365 data points, the distribution was assumed to be Gaussian due to this large sample size, meaning a parametric test could be utilized. For provider data pertaining to the third experiment, this assumption is not viable. Calculating the average number of patients seen in a year at either the operative or rehabilitative providers results in a sample size of 35 (one provider type per ZCTA for 35 ZCTAs). This is too small to assume a Gaussian distribution; therefore, nonparametric sign tests were performed on the provider data from this experiment with an alpha value of 0.05. Parametric tests were performed on the prevalence and death rate data from this experiment as this data was collected every tick leading to a sample size of 365 and an assumed Gaussian distribution.

Results

The first experiment involved limiting the distance patients could travel radially from their point of origin. This was tested for three different distances: d=3, d=5, and d=7. Data for prevalence rate, death rate, and change in population health over time were collected for each scenario. Unpaired t-tests of the prevalence rate data did not yield significance, with the smallest p-value being 0.1487. Unpaired t-tests of the death rate data yielded significance between the control and each scenario, with the p-values being less than 0.0001 for d=3, 0.0413 for d=5, and less than 0.0001 for d=7 (Figure 2). To evaluate changes in population health, the population was divided into six different health brackets and the number of patients in each bracket was counted at tick 0, 90, 180, 270, and 365 (Figure 3). Unpaired t-tests of each scenario compared to the control did not yield significance within this patient health data.

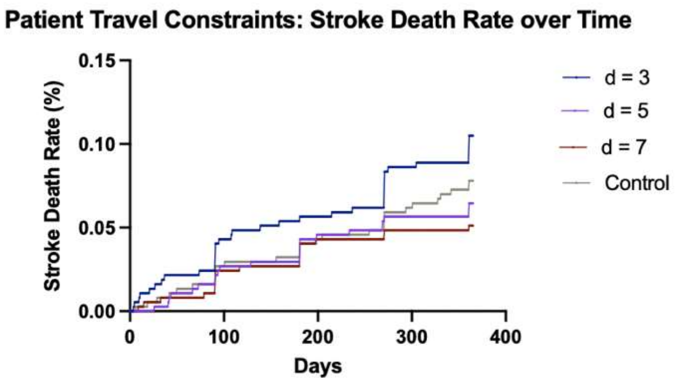

Fig. 2. Stroke Death Rate for Limitations on Patient Travel. Stroke death rate changes significantly ($p < 0.0001$ for d = 3, $p = 0.0413$ for d = 5, $p < 0.0001$ for d = 7) as a result of limiting the distance patients are able to travel from their point of origin. Three different distance limits were implemented: d = 3, 5 and 7 patches.

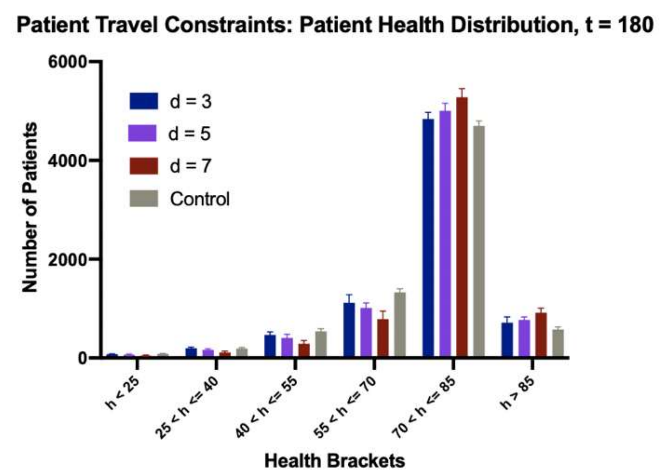

Fig. 3. Patient Health Distribution with Patient Travel Constraints. Distribution of patient health at day 180 for each distance the patients were able to travel from their point of origin. Patients were grouped into 6 brackets based on their health values, where h = health.

The second experiment ran on the model involved adjusting provider capacities to determine the effect of capacity on stroke prevalence and stroke death rate. Four factors were applied to adjust capacities including 110%, 68.24%, 68.24% applied to only operative providers, and 50%. 68.24% was the ICU bed capacity for Shelby County during the COVID-19 pandemic and was used to mimic a high-strain scenario. Unpaired t-tests of the stroke prevalence did not yield significance between the control and the capacity increase to 110%, operative capacity decrease to 68.24%, or the overall capacity decrease to 68.24%, yielding p-values of 0.4540, 0.4533, and 0.2460, respectively. The prevalence rate was significantly different between the control and the capacity decrease to 50%, with a p-value of 0.0122 (Figure 4). Unpaired t-tests of the death rate data yielded significance between the control and each scenario, with all p-values being less than 0.0001.

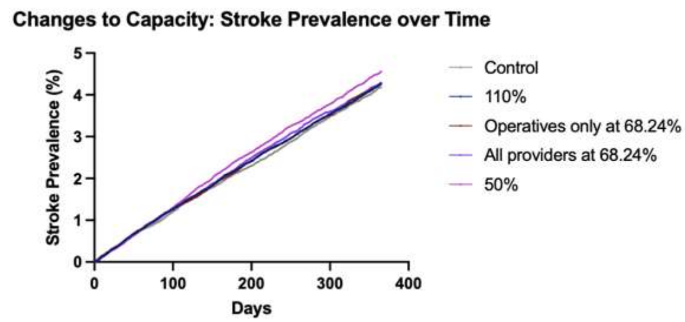

Fig. 4. Stroke Prevalence for Four Changes to Capacity. Stroke prevalence changes as a result of changing the capacity of providers. Four different changes to capacity were implemented: increasing all provider capacities to 110%, decreasing only operative provider capacities to 68.24%, decreasing all provider capacities to 68.24%, and decreasing all provider capacities to 50%. There is a significant difference ($p = 0.0122$) between the control and when capacity was decreased to 50%.

The third experiment involved adding operative and rehabilitative providers to the ZCTAs lacking them. The average patients seen per year was calculated for each operative and rehabilitative provider in each ZCTA before and after the addition of the new providers. An unpaired t-test of the prevalence rate did not yield significance. However, a nonparametric sign test was performed on the patients seen per year by ZCTA. This indicated a significant decrease in the patients seen in ZCTAs that already had operative providers when new ones were added to the ZCTAs lacking them (Figure 5). Despite a decrease in the number of patients seen per operative provider, the total number of patient-provider interactions increased by 658. This is equivalent to 65,800 visits to a healthcare provider. This demonstrates a patient population more evenly spread across providers rather than overly concentrated at certain ones.

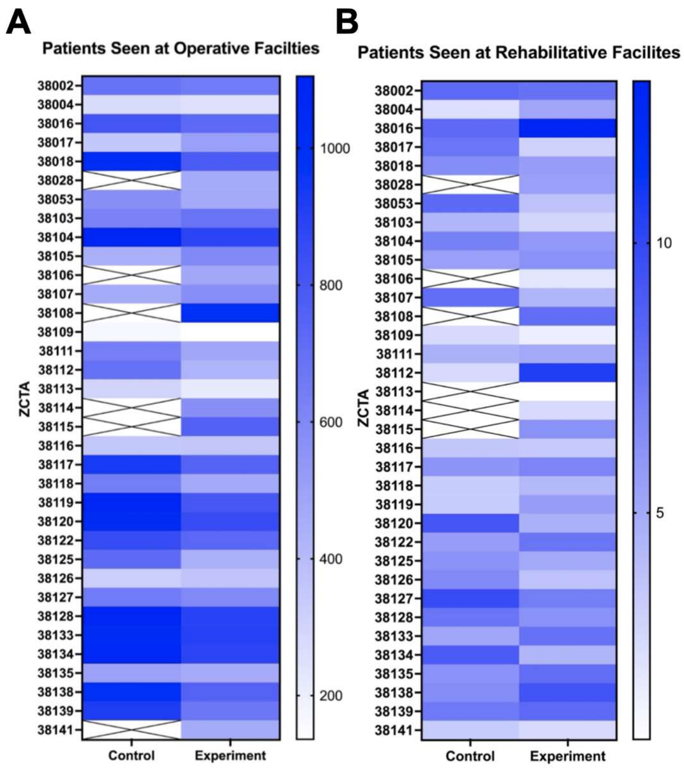

Fig. 5. Average Patients Seen Per Year at Operative and Rehabilitative Providers. A, Schematic of patients seen per year by operative providers before and after the addition of new providers. There is a significant decrease (p = 0.00088) in patients seen in the ZCTAs that already had operative providers when new ones were added. **B,** Schematic of patients seen per year by rehabilitative providers before and after the addition of new providers.

Experiment Validation

The ABM model was run 10 times, resulting in a stroke prevalence of 4.207% ± 0.23 and a stroke death rate of 0.1129% ± 0.025. The proposed model's death rate fell within one standard deviation of the expected value of 0.098%, and the stroke prevalence rate was within two standard deviations of the expected value of 4.56%[35]. These deviations were deemed to be acceptable due to their nearness to the desired values and the stochasticity of the model which causes variation in stroke prevalence and death rate from run to run.

<u>Discussion</u>

When patients were the most limited in how far they could travel from their point of origin (d=3), the death rate was significantly higher than the control. When patients could travel the furthest from their point of origin (d=7), the death rate was lowest (Figure 1). Although not statistically significant, Figure 2 displays how more patients had higher health values when they were able to travel furthest (d=7) than when they were most limited in travel (d=3). These results demonstrate how a patient's health or health outcomes will decrease with a lack of access to healthcare. This could imply that where there is a lack of public transportation or unreliable public transportation within Shelby County, patients' ability to get to a healthcare facility is hindered and their health will be negatively affected as a result. A second implication of these results is that healthcare facilities are not optimally placed within Shelby County to provide the best care possible to all portions of the patient population. Overall, these results emphasize the importance of a patient being able to access healthcare, whether through physical proximity, the use of public transportation, or another means of transit.

Telemedicine could be a potential solution to ensure a healthcare system that experiences these difficulties with patient access remains resilient during high-strain scenarios. Telemedicine has already been successfully implemented for stroke care in many healthcare systems, with telestroke becoming a developing component of the continuum of care for strokes[37]. If telemedicine could be effectively implemented into Shelby County's healthcare system, the distance a patient is from the nearest healthcare facility becomes less of a factor. This would increase healthcare system resilience by ensuring patient access no matter the scenario and eliminating barriers that result from patients being unable to travel to receive care, especially at the preventative level.

As demonstrated from the COVID-19 pandemic, another difficulty with patient access is in the limitation of provider capacities. This limitation can prevent patients from being seen in a timely manner, if at all. When provider capacities were reduced by 50%, there was a significant increase in stroke prevalence as compared to the control. This reaffirmed that having poorer patient access had negative implications for one's health, enough so that the likelihood of stroke increased. A potential solution to this issue rests in the recruitment of more providers at the preventative level. Advanced practice providers (APPs) like nurse practitioners (NPs) and physician assistants (PAs) are trained to provide the same level of primary care. The utility in these providers is that they require less hours of clinical practice for licensure and cost insurance agencies like Medicare less money[38]. By having more providers like APPs at the preventative level and thus increasing capacities, more patients will receive quality care and the likelihood of developing more chronic diseases like stroke will be less of a problem.

When ZCTAs missing operative or rehabilitative providers were supplemented so every ZCTA had all three types of providers, less providers experienced overcrowding. There was a statistically significant decrease in patients seen per year once new operative providers were added (Figure 5). With the addition of new providers there is less likely to be overcrowding in the providers that already exist, because patients now have more options for care. Ensuring that every ZCTA has access to an operative provider helps to spread resources to areas that are currently lacking them. As previously mentioned, high stress on providers can cause inadequate care for all kinds of patients. Stroke patients are particularly sensitive to strain, as survival is heavily dependent on how quickly a patient can receive care. By adding providers to these ZCTAs, it allows patients to be able to receive care quicker and at a closer location to their home than before. Ideally this will help reduce metrics like time to care and time to hospital so stroke survival rates can improve.

It is likely not feasible that Shelby County would be able to immediately implement the 6 operative providers shown in Figure 5. However a potential solution is the use of a mobile health vehicle that could travel to areas in the county where health care providers are lacking. Shelby County is currently in the early stages of implementing a mobile stroke unit for use in the county. This is part of a three year study run by the University of Tennessee Health Science Center[39]. If this initial project could be expanded to include more mobile units spread out around the county it could help reduce overcrowding of current providers and improve stroke response times.

Limitations

A limitation of the model as designed is that it only focuses on strokes and does not account for any other comorbidities. This means that changes to patient health and any provider visits that would result from another health condition are unaccounted for. Ultimately, any results or conclusions made from the use of this model could be made to the detriment of other areas of care. For example, resources may be taken away from other healthcare areas to be given to improve stroke care. A second limitation involves the model's strict focus on Shelby County; the model does not account for patient movement out of the county to receive care. Time is incorporated into the model through the use of ticks, but weekends are not taken into consideration. Weekends are times when most healthcare providers do not work and patients would be more likely to visit an emergency room or an urgent care facility. By adding in weekends to the model, it is likely that the patient-provider interactions would be different. Lastly, the model utilizes a scaled patient population, where 1 patient in the model represents 100 patients in reality. This may not accurately represent the real issues that Shelby County experiences. There are plans for the model to be run on a larger computer processing system at The MITRE Corporation with the full patient population and compare the results.

Future Work

The model as designed can be altered easily, by adding functionality to the code and incorporating more data metrics. The most important future work is to improve the accuracy of the model through the incorporation of more robust data metrics. By doing so, aspects of the model such as stroke risk or changes to patient health after seeing a provider could be more accurately represented. Another step to take in the future is to incorporate demographic information into the patient population to allow for even greater insights into the current limitations of Shelby County's healthcare system and make better recommendations as a result.

The provider data used within the model is Medicare data, which provides a rough estimate of the actual provider population. These providers also accept payment outside of Medicare, so this dataset is an adequate estimation to use for this model, but could be made more accurate in future iterations

Some of the most important metrics to add into the model are those that are time-based, such as time to care and time to treatment, since these metrics are critical to stroke care and outcomes. Adding in these metrics will better show the limitations healthcare systems experience for strokes in regards to time.

This model's incorporation of resilience could be greatly improved upon in future work. The work presented here touches on resilience qualitatively, but future iterations should evaluate resilience metrics such as duration to failure, duration to recovery, and performance before and after recovery in a quantitative manner. By doing so, ways that Shelby County's healthcare system lacks resilience would be better identified, and alterations to the model could be considered based on how they would impact the healthcare system's resilience metrics.

End Matter

Author Contributions and Notes

All authors contributed equally to the research.
The authors declare no conflict of interest.

Acknowledgements

The authors would like to acknowledge the support of Nathan Edwards and other members of The MITRE Corporation, as well as the support of the University of Virginia Biomedical Engineering Department.

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