B.O.H.C. (Boston Optimized Healthcare)

Team 9

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II. Executive Summary

The BOHC team developed a model of the healthcare system of Boston because we want to find the inefficiencies associated with medical service delivery to specific population demographics. The end deliverable of this project was a decision making software tool to be used by healthcare policy makers to help them evaluate the potential effects and benefits of a new health care policy on a specific demographic of patients in a specific location.

Low-income, elderly and chronically ill populations frequently use emergency department visits to access healthcare services because they are unable to afford health insurance or do not have access to a primary care doctor. This phenomena is especially alarming in Massachusetts, as the emergency department visit rate within this demographic is 10 percent higher than the national average. The BOHC team aims to use agent-based modeling to simulation the healthcare system in Boston and reduce overall costs by redesigning how underserved populations access healthcare services.

By creating a robust agent-based model BOHC's software program can identify the specific characteristics and needs of our target population: low-income, elderly, and chronically ill patients. The model can discern how these attributes may change over time to impact the overall healthcare system. A patient serves as an agent within the agent-based model with defined characteristics and input data points to dictate how the agent travels through the simulated healthcare system, cycling through specific institutions or alternative services to obtain optimum healthcare.

Given high levels of risk, uncertainty and cost, healthcare officials and politicians are reluctant to make meaningful changes to policy without substantial data. Our model relies on well-researched and documented agent parameters to determine potential strategy changes. Policy makers can use the BOHC software to input parameter changes according to a new healthcare policy and see the real-time effects on target demographics throughout the city.

III. Overview of Project

The problem BOHC is solving centers around patients not using the most cost-effective or efficient healthcare resources. Specifically, low-income and elderly patients who are chronically ill use the emergency department to receive medical treatment because it is free and they are guaranteed to be seen by a doctor. This misuse of medical services and resources leads to stress on the healthcare system. Additionally, it is expensive for hospitals and patients paying out of pocket and takes resources away from emergent patients for low-income populations to rely on emergency department services to access healthcare.

The problem objectives that BOHC is working with are creating a simulation to model the current status quo healthcare system in Boston. Additionally, our team wants to optimize and decrease the total cost associated with healthcare services while maintaining or increasing the quality of care for patients. BOHC uses agent-based modeling to simulate the healthcare system. Agent-based modeling is advantageous over other modeling methodologies for this problem because it allows the user to look at micro-level elements of an individual, model their interactions within the system, and extrapolate the results to a macro-level simulation. Agent-based modeling can capture emergent phenomena from micro-level interactions that cannot be replicated by a general analysis of system dynamics. Lastly, BOHC follows the objective to focus specifically on low-income, elderly and chronically ill populations as the target demographics for this simulation.

Our team chose to focus on Boston for multiple reasons. Firstly, Boston is considered a Smart City and has open data policies compared to other cities in the United States, like New York City and Philadelphia. Because of this, our team was able to retrieve and analysis healthcare data for the residents of Boston easily.

Additionally, across the United States, healthcare services for underserved populations are inefficient and expensive. In 2015, an estimated 30 percent, or $22.4 billion, of Massachusetts' total healthcare spending was categorized as wasteful. Low-income, elderly and chronically ill populations stress the healthcare system and are responsible for significantly increasing costs to healthcare institutions, especially due to unnecessary emergency department visits. From 2011 to 2017, the national rate of emergency department outpatient visits has declined roughly 2% each year; states are reducing their healthcare budgets without impacting patients and services or diminishing the quality of care provided. However, Massachusetts has not made significant progress in eliminating wasteful spending.

There is a high correlation between the median income of Boston's population and emergency department visits. In the Dorchester area, around 47 percent of emergency department visits are considered avoidable, with the most frequent illness diagnosed in the emergency department being stomach pain. Similarly, in downtown Boston, around 48 percent of emergency department visits are considered avoidable, with the most frequent illness diagnosed in the emergency department being acute sinusitis, or a sinus infection. Please refer to *Appendix 1* for visual map of income distribution and emergency department visits correlation.

Using agent-based modeling to solve health care system inefficiencies, specifically like the problem BOHC is trying to solve, is often discussed and talked about in systems engineering literature and research. However, to date, no systems engineering teams have developed a full-scale agent-based model to simulate the health care system in a city because of the complexity of the parameters and agent specifications. BOHC's model of Boston's health care system is the first of its kind and the team is excited about the progress made over the course of only one year.

By minimizing the amount of avoidable visits to the emergency department and keeping the target demographics out of the healthcare system cycle, there is substantial potential to enact meaningful change and reduce costs incurred by both public and private sector healthcare institutions.

IV. Method of Solutions

Specifications and Requirements

We developed our method by utilizing an agent-based simulation approach and reducing the problem down into its constituents. By bringing a very complex problem down to its parts, we were able to use real world data to model individual aspects of our simulation.

In our initial approach to modelling the problem, we used a spatial approach to creating the agents and city of Boston. Using a software called NetLogo, we were able to import a map of Boston and populate it based on the real locations of hospitals, people and medical services. We gave each of the agents we modelled certain characteristics like their age, gender, wealth, income, health level and insurance status. We also gave institutions that we were modelling certain characteristics as well such as services offered, cash on hand, number of beds, staff, and capacity. We also created a rudimentary map of the cityscape of Boston modelling major roads, highways and population centers. The agents we modelled would then follow the optimum path to the nearest institution that offered the services that agent needed and return back to there respective area on the map until they needed additional services. Our optimization concerned helping agents find the best service to utilize given their insurance status, provider set policy changes and cost (to both the patient and to the hospital). Upon discussion with the support staff, our advisor and team, we found it more beneficial to shift to a similar, but refined approach to solving this problem as described below. Please refer to *Figure 1* for an example of the user interface and model output from the NetLogo software application from the fall semester. In *Figure 1*, hospitals, agents and ambulatory services interface between the health care needs of the Boston area to output optimized results.

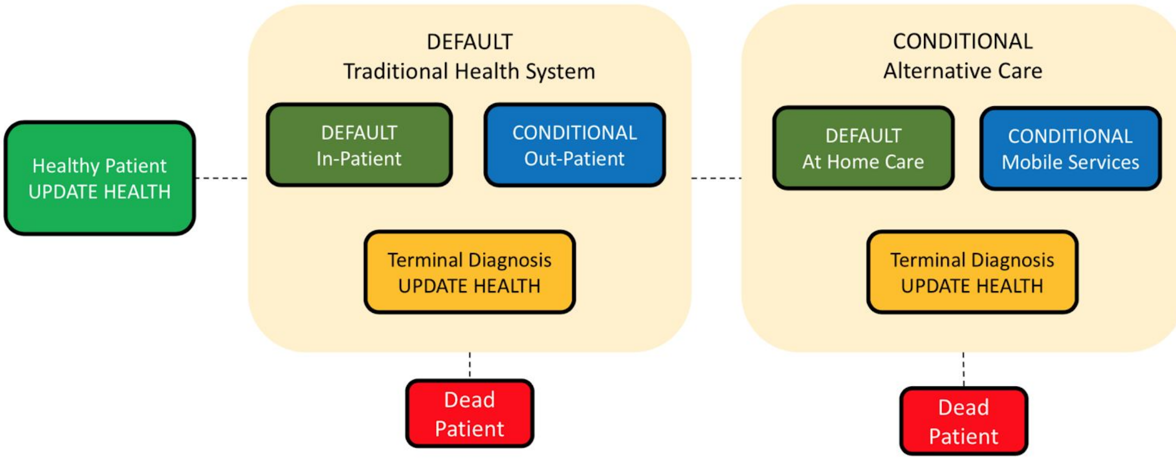
Figure 1: NetLogo Software Output

Although the spatial model was a good start to approaching our project, there were some limitations that warranted a pivot to a more generalizable simulation. One of the largest hurdles was accessibility of transportation data and road conditions in real time and present time. This would compromise the effectiveness of our model as a lot of the optimization had to do with quality of transportation networks. In addition, modelling the dynamics of a city wide transportation network that has cars, trains, busses, bikes, trolleys is a major undertaking in and of itself, and would not be realistically achievable in concordance with a health care system model in the timeframe of two semesters. We also scaled down the problem we were trying to solve to figure out the effectiveness of alternative services (medical deliveries, living assistance) to traditional healthcare (emergency department, hospital visits, pharmacies, urgent care). Perhaps the biggest advantage to switching our approach and software is scalability of our platform. The AnyLogic model can be generalized to include any city where certain data parameters and distributions are available/can be constructed whereas the NetLogo spatial model is hardcoded and cannot be easily modified or scaled to fit another city.

In the AnyLogic model, we first started by creating an accurate representation of the Boston agent population and using United States Census data and NHATS (National Health and Aging Trends Study) data. We obtained data concerning income distribution, age, gender, and rates of the following top five chronic diseases: arthritis, diabetes, heart disease(s), high cholesterol, and hypertension. We used this data to then construct distributions which we then applied to the 65+ agent population of Boston. Similar to how we did in the NetLogo spatial model, we gave each of these agents parameters to model various characteristics. We did the same for the healthcare institutions by giving each institution functions and variables that modify parameters within the agents upon use of the specific service.

Another important aspect of our model is the agent statechart. This statechart helps give our agents intelligence based on a utility function created to drive agent-institution interactions. This statechart includes structures, such as states, compound states, and transition parameters to describe when an agent would move into the next state. Each state described a type of institution that an agent would go to when he/she was in need of medical care. Our simulation allows one to set certain policy constraints such as out-of-pocket costs (deductibles) and types of care that are under coverage for low and medium income elements of the population (the populations most likely to be under the care of public insurance policy). Please refer to *Figure 2* for a simplified version of the AnyLogic agent statechart functionality. Please refer to *Appendix 2* for the model's detailed agent statechart.

Figure 2: Simplified Statechart for Individual Model Decisions



Specific Classes and Knowledged Used

As a team, our members utilized the skills and knowledge learned in several Penn Engineering classes. The BOHC team uses java programming skills, understanding of functions and data structures, as well as hierarchy learning in CIS 120. We also analyzed the behavior of dynamic systems using skills learned in ESE 210. In order to fully flesh out the engineering standards and ethical concerns we needed to take into account, the team relied on skills learned in EAS 203. Additionally, we needed to understand how to build an agent-based model and how to use agent-based modeling methodology and failure analysis, as well as agent-based modeling softwares, like NetLogo and AnyLogic. The team learned these skills in Professor Barry Silverman's courses ESE 420 and ESE 590.

Caroline and Brian took Professor Barry Silverman's class ESE 590. JJ had taken ESE 420. The entire team had taken CIS 120, CIS 110, EAS 203 and ESE 210.

V. Self-Learning

Two of our team members had experience with agent-based modeling theory and all team members read theory overviews online. Then, we learned about methodologies and how to code in NetLogo, the software we are using for the first-semester of our project. For agent-based modeling theory and methodologies, BOHC read numerous papers and studies recommended to us by our advisor. By reading and studying these reports, the team understood the foundations of agent-based modeling.

First semester, our advisor recommended NetLogo, which had robust backend capabilities and the best front-end user interface. NetLogo was preferred for spatial modeling and visualizing the agents using paths and transportation in a city. The software also has an R-compatible package that we had intended to use for data analysis. A few months in, we were up to speed on NetLogo literature and felt generally comfortable coding the software. After a few more meetings with our advisor, we found that despite a robust and intuitive programming software, we struggled with the flexibility to implement additional nodes that represented novel practices.

Coming back into second semester, we pivoted from using NetLogo to AnyLogic. All team members had some basic familiarity with Java, which was one reason we decided to switch software. AnyLogic uses a Java back-end to describe interactions between agents, which meant the team felt more comfortable to begin our analysis. As the semester progressed, we gradually had to learn about inheritance in software because different agents (of different economic status, age status, sickness) had to inherit different characteristics and abilities from the parent class of our agent.

The pivot away from NetLogo was initially very difficult, given the depth of experience and development of our model in that software. We had to distribute responsibilities differently, and ramp up to speed quickly so that we could make progress in AnyLogic. After we all learned AnyLogic, we successfully translated the most applicable elements from our NetLogo model into AnyLogic.

After we had learned about our new software, we then used R to describe the distributions of characteristics to accurately represent our population. Brian, Dillon and Adam had experience with this language, but all members learned basic familiarity to ensure consistency. These distributions were then inputted into AnyLogic to represent our populations, which required some cross-language capabilities. By the end of the project, all members had exposure to NetLogo from first semester, and much more extensive exposure to Java's use in agent-based modeling. This has proven to be very practical, as most team members require some software capabilities next year in the workplace.

VI. Design and Iteration

In terms of design, we primarily had to first decide on the type of model that we wanted to implement. We decided early in our design process to use agent-based modeling. Our design refers to the conceptual model, which outlines the locations and states an agent can occupy. These locations and states are determined by the agent's parameters, such as income level, race, chronic conditions and their behavior guided by a utility function aiming to reduce cost and maximize access to healthcare. We had initially attempted to use an SIR (Sick Infected Recovered) model but this model did not encompass all the broad potential outcomes of a real-life scenario. We switched away because our advisor recommended against it, after we had tried our first implementation.

We switched away from our initial model because it did not account for an agent-institution selection protocol, essentially how an agent's utility function affects his or her decision making. After changing this, we then defined a function, not yet a utility function, for agents to filter through specified layers of decision making based on their initial conditions and preferences. These layers included insurance, urgency, medical need and transportation. After the filtering occurs for each individual agent, the agent is then placed into the most optimal institution. As for the conceptual flow through the diagram, we implemented this through our conceptual flow-chart model.

In the updated version, with a utility function, we follow similar parameters to the above, but these also include numerous parameters, which include (but are not limited to), diet, exercise, physical health, health level, willingness for care, has a hospital in range, mental health status, number of illnesses, status on chronic medicine or one-time medicine, and then parameters for the intensity of care for arthritis, hypertension, diabetes, high cholesterol and heart disease. We defined these parameters based off the data we had in our NHATS data, which we used to determine distributions to model our population. We also expanded the scope of our institutions and services offered to offer more in-depth scenarios. These institutions in the alternative care section include, but not limited to:

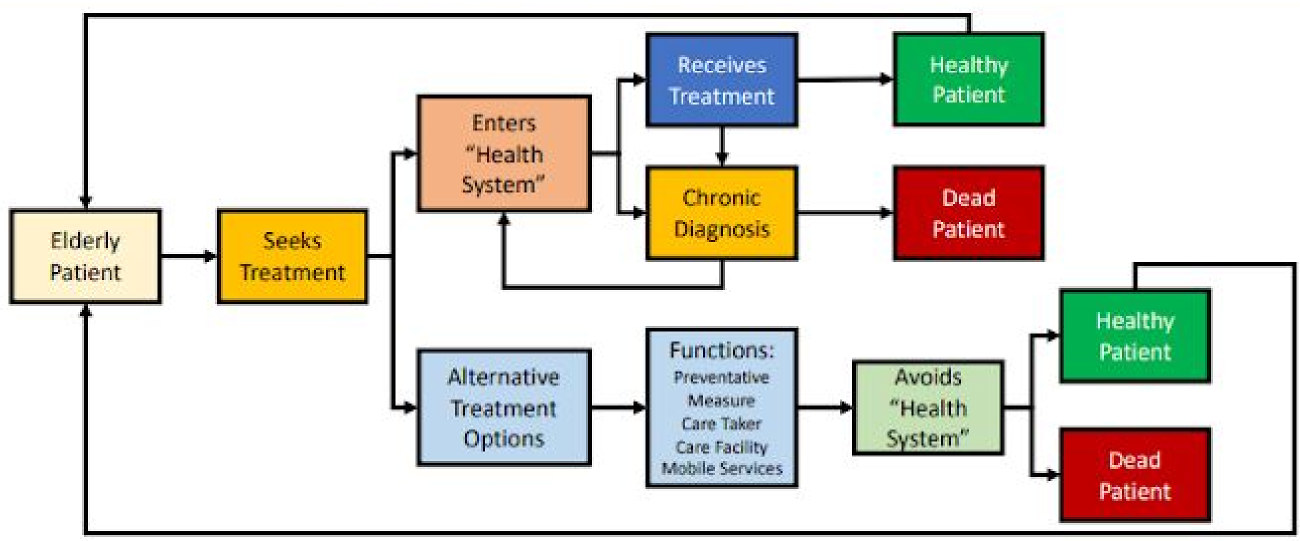
1. At-home care for a terminal illness
2. At-home treatment for chronic illness
3. Living assistance, such as a nursing home
4. Social assistance, such as public housing or other government services
5. Refer to the Appendix for a screenshot of all the parameters and institutions in our model.

As for the updated design, we begin with an elderly patient who seeks treatment, which is the start of our system design loop. (1) If the agent enters the 'health system' which means the traditional route, or emergency room, then he receives a treatment for a one-time illness and recovers until he becomes sick again. If he receives a chronic diagnosis, this patient continually will enter the costly 'health system', resulting in high costs, ineffective treatments and inefficient treatment, until he dies. This is the loop that our project primarily hopes to avoid, because this is highly costly and lacks productivity. (2) If the agent seeks alternative treatment options, there are four main functions:

1. Preventative Measure: meant for disease prevention as opposed to disease treatment
   (1) 'Health promotion' which refers to current, non-clinical life choices like eating healthy meals and exercising daily to promote overall well-being.
   (2) 'Specific Protection' refers to activities that target a type or group of diseases, and can be avoided by maintaining hygiene, routine check-ups
2. Caretaker: a member of a person's social circle who helps them with activities of daily living, typically in old age, disability, disease or mental disorder
   Managing medications, talking to doctors on someone's behalf, bathe, dress, bills
3. Care Facility: primarily refer to nursing homes, a type of residential care for around-the-clock service for elderly and ill individuals
4. Mobile Services: refers to the practice of medicine and public health who travel to less-developed regions, for those who cannot receive treatment at home (in terms of bus services) or with traveling doctor-and-nurse networks who can travel to specific homes

Please refer to *Figure 3* for a simplified version of an elderly patient's potential paths.

Figure 3: Simplified Version of Elderly Patient Paths



These four services are the goals of our model, because the costs are lower, treatment times are shorter, and recovery is generally better. If the patient recovers, this is the ideal outcome - avoiding the 'traditional health system.' We arrived at this model through developing a lens on the dynamics of healthcare, and through a recommendation from our advisor.

As for the standards we followed in our design, we had to follow three main principles to ensure our model functioned properly. First, for interoperability standards, this meant our model had to format correctly and function properly across systems. The US DOD defines TENA, or Test and Training Enabling Architecture, to promote integrated testing in simulation-based design, which is largely applicable to our project. The relevant IEEE standards include IEEE 1278.1-2012, IEEE-1516.1-2000, IEEE 9945-2002, IEEE 13210-1999. For simulation specifically, Simulation Interoperability Standards Organization (SISO) analyzed simulations and determined that interoperability saves 3% of budget and time, due to lost productivity.

Second, we had to follow end-to-end information flow standards, which protect the confidentiality of information manipulated by a computing system. Given the complexity of patient information, this formally verifies that the system follows these policies. Since AnyLogic is a Java based language, this isn't an issue - since today's system software consists of both C and assembly programs. The relevant standard for this is ISO 21089-2004, which discusses protected-health-information (PHI).

Last we follow life-cycle management policies, which address systems concepts in life cycle simulations. These are fairly straightforward, and are primarily definitions that describe how concepts relate to detailed process standards. The relevant standards for this include ISO/IEC TS 24748-1:2016, ISO/IEC/IEEE 15289:2015.

AnyLogic is a software used in healthcare policy planning, resource utilization (such as in mining), scheduling and process flows (logistics). The software's standards and requirements are that Java 8.0 Standard Edition or higher is installed. Since the software is already used in healthcare policy, we don't run into issues related to protected-health-information. The software can read and modify Excel files, and also has an important feature with Geographic Information System files (GIS), which are designed to capture, store and analyze spatial data (such as a city). These can include space-time information, latitude, longitude, and elevation information. This is a new technique, given the improvements in satellite imagery - satellite images now can take images hourly with pixels less than a 12" x 12" - enough to distinguish a piece of paper in a parking lot. If we were to conduct this project in five years, there will likely be code to represent individual cities on a block-by-block basis with detailed information on walking, public transport and driving capabilities.

VII. Societal, Global and Economic Impact

In an overarching sense, this project ideally has vast societal and economic impact in terms of reducing healthcare and aiming to provide more consistent, lower cost healthcare. Given our stakeholder group, which includes medical institutions, individuals, political institutions and corporations, we see vast potential to offer more specialized recommendations to improve access for our target population. Refer to Appendix IV for a detailed list of stakeholders. We hope that the optimization of the healthcare system results in net-positive benefit on society - maintaining quality of care while reducing costs, or even improving quality of care. BOHC's model allows different packages and abilities to be offered to our stakeholder groups, which can then be modeled to understand economic and healthcare outcomes. We prefer this flexibility, because detailed data can be applied for specific cities or populations.

In the societal sense, our model targets the most costly sector of society, which is the elderly, low income and chronically ill. This can be applied in a democratic context - similar to 'no child left behind' - such that all cohorts in the country are equally treated. Our aim is to rectify the structural costs and gaps in care, across the country. This has vast societal implications, such as reduced cost of care (more money can be used for research), improved productivity (less chronically ill translates to increased output, such as GDP or trade) and improved happiness (those who are healthy are more productive, and thus happier).

In the global sense, we hope to use the flexibility of our model to target global populations to refine these healthcare systems. Our project can model the expected benefits and costs of a variety of healthcare options, which can then be used across the global context. Given that different cities and countries disclose healthcare differently, we anticipate more progressive cities to benefit more. The model's context can vary, but the baseline applications are robust.

The potential ethical issues that correspond to this project center around the accuracy of our data. Essentially, our dataset only includes individuals who have disclosed their economic and health status, which may not accurately represent the population at large. For example, given that not all patients report, there is a cohort of population who we may misrepresent. This issue is not easily resolved, but we aim to include more flexibility for these populations. Similarly, our agents can undertake both harmful actions (such as drug-use, malnutrition, lack of exercise) and beneficial actions (self-care, preventative medicine) which can affect our representation of their data. Again, we aim for model flexibility so we can encompass a large portion of our target population. Last, hospitals and institutions don't disclose the costs and efficacy of care with the highest degree of accuracy, due to their public spotlight (rising healthcare costs). Therefore, we have to use the given data and medical techniques to represent our model population.

VIII. Summary of Meetings

Fall Semester

We met as a team weekly, typically on Monday afternoons from 3-4:30PM. This was the time that all of us had available, so worked on our model framework for the first few meetings, and then shifted into formulation and design. Towards the end of the semester, we met more frequently and for longer durations, typically on the weekends for five to six hours. During these meetings, all members participated equally, but tasks and responsibilities varied. Brian and Caroline primarily worked on design and deliverables while Dillon, JJ and Adam worked more on the coding and translation from design into code. In mid-November, we rotated responsibilities to ensure all of us were capable both in design and NetLogo coding. Despite late meetings and busy schedules, we maintained a friendly working dynamic.

For meetings with our advisor, Professor Barry Silverman, we first considered New York as our first city, but then Professor Silverman decided against this because of data publicity. After shifting to Boston, we worked for a few weeks to gather data and translate our design based on differences in city. As the semester progressed, we clarified our design and objectives, and refined our model per his recommendations.

As for meetings with Senior Design staff, our early meetings with Sid consisted of explanation our current routes and design. As the meetings progressed, we considered more versatility to ensure our model had broader implications. In our TA meetings, we primarily discussed objectives and deliverables. These meetings clarified objectives for the semester, which was very helpful.

At the end of the semester before Demo Day, we worked both independently and in groups to refine our model and continue our broader progress. We met more frequently with Profession Silverman, given his valuable insight and experience in agent-based modeling for healthcare. This progress was consistent and not back-ended. By meeting more often, we reduced our final burden in late March and early April. We will also continue to meet with Sid and the TAs independently to continue clarification and improve our deliverables.

Spring Semester

We met as a team twice a week, given that we had to switch our software and essentially reset our project in terms of actual implementation. Therefore, we had to make considerable progress to code and implement out design into the new software, AnyLogic. We met Mondays from 1-2PM and Fridays from 1-4PM every week section semester. The first few meetings involved shifts in design and formulation, to have a broader context and flexibility. In the run-up to final Demo Day, we met more than twice a week to ensure we had a working, viable model for this. All members coded in Java for AnyLogic, and a few learned R to translate our dataset into working assumptions for our model.

For meetings with our advisor, Professor Barry Silverman, he suggested we shift our software and lens to be broader with AnyLogic. We had standing meetings with Professor Silverman on Mondays from 2-3PM. After shifting to AnyLogic, we worked for a few weeks to gather data and translate our design due to inherent differences in software and modeling capabilities. As the semester progressed, we refined our model. We met with Professor Silverman the week before the Demo Day to present our results and poster to him, which proved to be very helpful to ensure our model had accurate results.

As for meetings with Senior Design staff, our second semester meetings with Sid were more directed - especially given our shift. As the meetings progressed, we had to ensure that we were on track in terms of project progress. In our TA meetings, we primarily outlined deliverables, in terms of the class. These meetings clarified our semester plan, in terms of checkpoints and on-time milestones. We attempted to maintain these guidelines and deliverables on time, both so that we knew we were on track with the broader class and so that we would encounter issues and problems before Demo Day.

Given the tight timeline with Demo Day, all members worked to first ensure a working model with output, and then to further refine our model and check accuracy. We met more frequently as a team, which helped to push forward, and with Professor Silverman, given his experience and suggestions. This progress was back-ended at times, but overall was consistent. After Demo Day, we met as a team to ensure our model outputs were consistent, and continued to refine the model further. We plan to send our model and paper to our advisor as well.

IX. Final Schedule with Milestones

In terms of team progress, we are satisfied with our overall team progress. We started with a structural framework of what agent-based modeling was, then defined our design, as outlined above. After defining our design, we worked to implement this into NetLogo using the framework our advisor gave us. Given that we had to pivot away from NetLogo, we made considerable adaptations with the capabilities of our model. Our model outputs results that are verified and validated (V&V), in terms of the costs of care and the relevant treatment types. We expanded services and institutions in our model, and also expanded the framework to be more flexible for different data fields.

Please refer to our final team schedule listed below.

<u>January</u>: developed a framework that now suits the switched software, and familiarized broadly with the shift to AnyLogic. For this, we had to all learn the documentation and formatting of the software, along with running basic models that AnyLogic offers.

<u>February</u>: code model into AnyLogic with accurate output

We had to create the parameters again, which meant defining all the potential factors that can dictate a user's filter function - we used a filter function before we switched to a utility function. We also had to code into the software a framework to filter through the respective institutions. We had to iterate through this numerous times because of not considering or analyzing parameters correctly. For example, we struggled with how to consider and quantify willingness-for-care. To do this, we had to first consider functions that characterize treatment in a realistic manner. After doing this, we had to create distributions given agent parameters (which occurred in March).

<u>March</u>: implement NHATS data and census data

To implement the NHATS data, we ran regressions on the NHATS data. This was difficult, because the files weren't formatted correctly to input into R. We therefore had to translate the PDFs into CSVs, which was highly manual and then create distributions. It was difficult to tease out covariances and accurately describe each parameter, but we eventually succeeded with that. Afterwards, we revised our filtering function to a utility function - which required additional data segmentation and characterization of agents. We then had to work on relevant outputs for our model, such as Daily Care Costs (which we display with our model).

<u>April</u>: refine output and prepare for Demo Day

For this section, we had to consider the most relevant outputs for our model. We decided, after recommendation from our advisor, we decided on the factors listed below.

<u>Cumulative Care Costs</u>: total costs of care provided in our system. We can analyze the slope to find that our marginal costs are decreasing, meaning our model is working

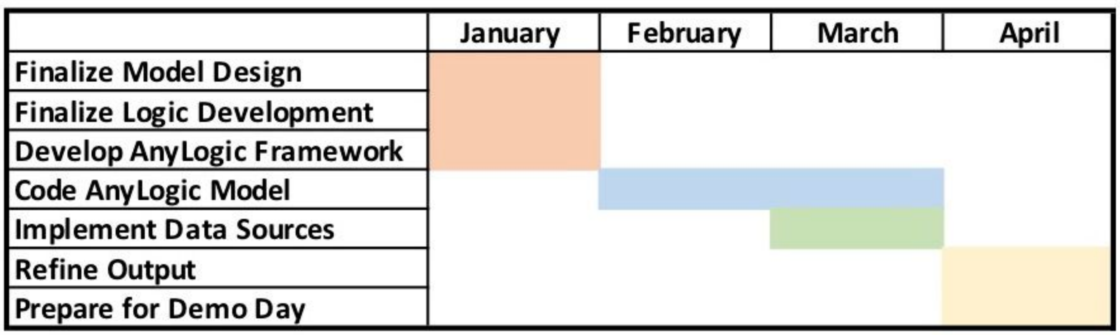
Daily Care Costs: daily cost of care in our system, which spike initially due to high emergency room exposure. These then decrease as agents become aware of alternative forms that are more efficient and favorable for the agent.

Fraction of Visits: breakdown of the type of visit, between the Emergency Room (RED), At-home Visits which are a representation of alternative forms (GREEN) and daily inpatient care visits which are patients admitted to the hospital (BLUE). Importantly, the number of inpatient care visits decreases.

Daily Visits: breakdown of the total number of visits by institution type, which are the same types as above. We see that inpatient visits decrease in frequency, while daily-at-home visits increase - which is the main goal of our policy.

Please refer to *Figure 4* for our team's Gantt chart of BOHC's milestones and accomplishments.

Figure 4: BOHC Finalized Gantt Chart for Project Development



X. Discussion of Teamwork

Throughout second semester, our work allocation was fairly similar to the allocation that we had first semester. There were a few tasks that mainly occupied our time: design, deliverables, data analysis, software development and coordination.

Design: In terms of project design, this task first semester was accomplished by Caroline, Brian and JJ, with help from Professor Silverman. The two initially built an SIR, Sick Infected Recovered, model but then shifted away from his recommendations due to lack of optionality. JJ, Brian and Caroline continued with design into second semester, shifting instead to a broader, alternative treatment plan. Having two members assigned to this was beneficial, given that either could engage with our advisor to ensure our model design was accurate and representative of real-life behaviors.

Deliverables: As for deliverables, this refers mostly to the deliverables we had for Senior Design (such as presentations, posters) but also to deliverables for meetings with our advisor (such as a suggested design or working model). Caroline was in charge of all team deliverables and was assisted by Brian. The group felt Caroline and Brian were on-time and responsible with deadlines, so this task was allocated to those two. The two felt proud of the deliverables and didn't run into any issues with deadlines, so we were happy with overall progress on this.

Data Analysis: As mentioned above, our design shifted in early second semester, so we had to update our design. Given that AnyLogic has different parameters and integration capabilities, Dillon and Adam needed to reanalyze the data from the team's two databases NHATS and the US Census data in order to calculate the distributions for population-based numbers that were implemented within our AnyLogic model.

Software Development: Since AnyLogic is a Java-based software, the members with the most coding experience in Java felt most comfortable with the coding portion. JJ, Dillon and Adam were responsible for this portion. During the coding sessions, Brian and Caroline clarified the model design to ensure accurate translation into code. The coding portion took slightly longer than expected, given the team's slight inexperience with the software. Overall, the translation from design to code was successful, and the team agreed upon the outputs that we wanted for our model.

Coordination: We assigned one member to this task, to ensure the group was on-time with meetings, that we were aware of deadlines and that responsibilities were fairly distributed. Caroline was in charge of all coordination and ensured cohesiveness in progress throughout the semester. This meant assigning tasks, scheduling meetings, booking rooms, reminding members about advisor meetings, etc.

Please refer to *Figure 5* for the breakdown of second semester contributions.

Figure 5: BOHC Team Member Contributions

Team Function	**Adam**	**Brian**	**Caroline**	**Dillon**	**JJ**
1st Priority	Data Analysis	Design	Head Design	Software Development	Head Software Development
2nd Priority	Software Development	Deliverables	Head Deliverables	Data Analysis	Design

Distribution of tasks was equal in the long-term. At times, certain team groups had more responsibility, such as design making the model early on, while the coding team had late nights to translate this into code when approaching Demo Day. We were very comfortable with this, and maintained flexibility to ensure better output.

In terms of our overall team dynamic, we feel very comfortable with our working dynamic. There were, of course, times when members were frustrated with either inavailability or difficulty in delivering on time, but that's to-be-expected in a long-term project. We had a major pivot with change in software, but this was taken in stride due to early efforts from coding and design. We're very happy of our end product, and enjoyed the team dynamic throughout the semester.

XI. Budget

The BOHC was able to successful spend zero dollars on our project. The software tools our team used, NetLogo and AnyLogic were acquired for research and academic use. Professor Barry Silverman was able to secure each team member academic and research licenses for both software packages for free through the University of Pennsylvania.

Additionally, the BOHC team did not need to take a trip to Boston to speak with stakeholders because Professor Barry Silverman attended a meeting with his main point of contact for agent-based healthcare modeling at Harvard. At this meeting, Professor Silverman was able to ask his contact all of the questions we would have asked him, had we gone to Boston to speak with him. Because of this, our team was able to avoid the additional travel expenses of going to Boston for stakeholder meetings.

Lastly, our main stakeholder contact, Dr. Shreya Kangovi, teaches at the Perelman School of Medicine and we did not have to travel or incur any additional expenses to speak with her and get her feedback on our software.

XII. Work for Second Semester

The BOHC team's work during the spring semester is discussed in detail in section *IX. Final Schedule with Milestones*. The main goals we needed to accomplish as a team in the spring semester was to pivot from NetLogo to AnyLogic, getting in touch with reliable stakeholder contacts, and iterating our model's design to be the most effective and accurate representation of Boston's health system.

Our team knew that we needed to change the structure of our model and switch the software modeling package we were using by the end of the first semester. When our team returned after winter break, we were able to successfully implement the original design logic into AnyLogic. Our team members first needed to get familiarized with the new programming language and modeling software, but after the first few meetings we were able to make good progress. Most of the semester was devoted to iterating and modifying our models logic and design based on input from our advisor and stakeholders. Please refer to *Appendix 3* for our finalized user interface and parameter settings.

The team simultaneously analyzed and implemented the appropriate data from the US Census and NHATS databases in order to populate our model's agent parameters. A significant amount of time was spent iterating and finalizing the best method for extracting the necessary data from these databases and implementing the correct distribution into the agent-based model to allow the agents to make the correct decisions based on their parameters. Please refer to *Appendix 4* for the output of the BOHC model based on example policy changes.

The BOHC team finalized our stakeholders for this project to be five distinct groups: hospitals, medical institutions, political institutions, individuals, and corporations. All of the main hospitals in the Boston area are considered to be stakeholders in this problem, including Beth Israel Medical Center, Boston Children's Hospital, and Massachusetts General Hospital. Medical institutions such as, ambulatory care centers, dialysis clinics, nursing homes and urgent care centers are crucial stakeholders in this problem focusing on medical care delivery. The City of Boston, the Boston Public Health Commission and the Boston Health Care for the Homeless Program are specific political institutions that are invested in solving this problem. Additionally, individuals ranging from doctors and nurses to service providers to patients are considered stakeholders for BOHC's project. Lastly, corporations such as insurance companies, pharmaceutical companies and industry suppliers will be affected by BOHC's end software deliverable.

XIII. Standards and Compliance

As for the standards we followed in our design, we had to follow three main principles to ensure our model functioned properly. First, for interoperability standards, this meant our model had to format correctly and function properly across systems. The US DOD defines TENA, or Test and Training Enabling Architecture, to promote integrated testing in simulation-based design, which is largely applicable to our project. The relevant IEEE standards include IEEE 1278.1-2012, IEEE-1516.1-2000, IEEE 9945-2002, IEEE 13210-1999. For simulation specifically, Simulation Interoperability Standards Organization (SISO) analyzed simulations and determined that interoperability saves 3% of budget and time, due to lost productivity.

Second, we had to follow end-to-end information flow standards, which protect the confidentiality of information manipulated by a computing system. Given the complexity of patient information, this formally verifies that the system follows these policies. Since AnyLogic is a Java based language, this isn't an issue - since today's system software consists of both C and assembly programs. The relevant standard for this is ISO 21089-2004, which discusses protected-health-information (PHI).

Last we follow life-cycle management policies, which address systems concepts in life cycle simulations. These are fairly straightforward, and are primarily definitions that describe how concepts relate to detailed process standards. The relevant standards for this include ISO/IEC TS 24748-1:2016, ISO/IEC/IEEE 15289:2015.

AnyLogic is a software used in healthcare policy planning, resource utilization (such as in mining), scheduling and process flows (logistics). The software's standards and requirements are that Java 8.0 Standard Edition or higher is installed. Since the software is already used in healthcare policy, we don't run into issues related to protected-health-information. The software can read and modify Excel files, and also has an important feature with Geographic Information System files (GIS), which are designed to capture, store and analyze spatial data (such as a city). These can include space-time information, latitude, longitude, and elevation information. This is a new technique, given the improvements in satellite imagery - satellite images now can take images hourly with pixels less than a 12" x 12" - enough to distinguish a piece of paper in a parking lot. If we were to conduct this project in five years, there will likely be code to represent individual cities on a block-by-block basis with detailed information on walking, public transport and driving capabilities.

Our team did not need to compile with HIPAA's strict standards for data privacy and protection in regards to personal and individual health information. Boston is considered a Smart City and has open data policies for many different types of data sets. Because our team chose to look at Boston and its residents, we were able to access distributional data on specific illnesses and health data through the NHATS database and avoid needing to compile with HIPAA standards.

XIV. Business Analysis (M&T)

Broadly, the rate of growth in health care spending has outpaced the GDP rate, inflation and population since the 1940s - growing at between 4-7% per year from 1940-1990. The share of healthcare spending as a percent of GDP increased from 4.5% in 1940 to 12.2% in 1990, which makes the US an outlier on the global scale. This problem is highly complex - health care spending occurs in diverse and complex ways, so this problem is highly relevant.

After the Great Recession, spending on US healthcare slowed down - likely due to the long-term effects of an economic slowdown. Generally, individuals choose to spend less on health care because insurance policies become less generous, because providers cut back on investments (so available spending decreases) and because states with budgetary cuts scale back on Medicaid and health programs.

Our model aims to improve quality of life and avoid preventable deaths, while reducing costs overall. With a backdrop of an increasing population and longer lifespan, models of treatment delivery - such as at-home, in hospitals, in emergency rooms or mobile solutions - are rapidly changing. Our team recognizes that prevention is better than curing diseases, both due to lower costs and due to increased quality of life. Given that our population is chronically ill, this isn't an option because we have to understand patients who enter the medical system repeatedly.

More specifically, agent-based modeling has applications in a variety of fields that include the factors listed below.

<u>Planning and Resource Allocation</u>: Agent-based modelling systems can focus on the coordination and scheduling of nurses, doctors and aids. These systems can also focus on medical resources, such as limited medical instruments or mobile care units.

<u>Remote Care</u>: Agent-based modelling systems can focus on remote monitoring of patient status, to maintain points of contact with the health care system.

<u>Decision Support Systems</u>: Agent-based modelling systems have an important application in execution of healthcare practices - such as modelling treatments and preventative care.

Our model has crucially important business implications, which include the factors listed below.

<u>Capture Emergent Trends and Phenomena</u>: Given that our user data is updated frequently, our model can decouple and then understand properties that are complex to understand on a macro-level. For example, if agents cannot access a hospital (which could results from agent and transportation difficulties, or poor weather), there may be a substantial increase in hospital visits and frequency in the coming days. Real-world patients tend not to behavior linearly. Rather, they take actions that are path-dependent, changing their behavior based off current

conditions. Thus, given the changing data set, our model can capture early bottlenecks and represent these empirically in terms of cost and treatment breakdown.

Healthcare Spending: As mentioned above, health care spending has increased over the last 80 years substantially due to more treatments options, rising medical costs and repeat-use cases. By offering alternative, specialized treatment plans, our solution aims to improve efficiency challenges in healthcare delivery. By using a systematic model to represent the factors that determine an individual's healthcare decisions, we aim to produce outputs - primarily costs and treatment breakdowns - to represent patients' impacts on the healthcare system. By decreasing healthcare spending, the increased budget can be used to both:

> *Increase R&D*: Similar to Johnson and Johnson's $30B tax break which is all going to R&D, increased budgets can be used to develop novel treatment practices, develop niche drugs and research both chronic and rare diseases. Eventually, this investment will improve quality of care.
>
> *Improve Quality of Care*: by extending additional services to patients and boosting health outcomes. For example, a hospital with significant surplus can offer more preventative options to patients.

Improve Quality-of-Life (QOL) and Productivity: Health-related productivity losses can explain the heterogeneity in economic output. Broadly, healthier employees are more productive - due to more days on the job and increased mental clarity. For example, normal-weight men miss 3.0 days each year due to illness or injury, while overweight men miss 4.68 days each year. This effect tends to magnify as individuals age, so there's a significant loss in productivity associated with poor health.

Affordable Patient Care Act (Obama Care): This 2010 bill mandated reduced costs and increased accountability and transparency for quality of care. Chronic illnesses, as mentioned, place the highest costs on health care budgets due to repeat visits, so systems modeling can be used to improve (or maintain) quality while reducing costs. Thus, given this new regulation, we see the importance of cost monitoring and reporting as increasing going forward. Therefore, by using a simulation similar to ours, hospitals and executives can better understand the cost breakdown by sector within hospitals and treatment centers. With the pay-for-service model sticking around, this will likely become increasingly important in the future, given that each service performed on a patient is going to be calculated on a profit-and-loss level basis.

Using our Boston data as a backdrop, the agent's attributes can be segmented into cohorts of agents who all behavior similar. These patients can then be treated on a more targeted basis, given socioeconomic (such as income, homelessness), behavioral (smoking, diet), and physical (overall health, type of illness). From this information, our project can model different treatment options, and then suggest the most optimal treatment option based off different parameter inputs. Overall, by offering alternative treatment options, our model aims to reduce costs of care. For managers, the goal of this project is to improve allocation issues and improve health outcomes in patients.

XV. Conclusion

The BOHC team aimed to solve a problem centered around patients not using the most cost-effective or efficient healthcare resources. Specifically, low-income and elderly patients who are chronically ill use the emergency department to receive medical treatment because it is free and they are guaranteed to be seen by a doctor. This misuse of medical services and resources leads to stress on the healthcare system. Additionally, it is expensive for hospitals and patients paying out of pockets and takes resources away from emergent patients for low-income populations to rely on emergency department services to access healthcare.

Our team set out to optimize and decrease the total cost associated with healthcare services while maintaining or increasing the quality of care for patients. BOHC used agent-based modeling to simulate the healthcare system. The BOHC model focuses on low-income, elderly and chronically ill populations who suffer from the five most common chronic illnesses.

Using agent-based modeling to solve health care system inefficiencies, specifically like the problem BOHC is trying to solve, is often discussed and talked about in systems engineering literature and research. However, to date, no systems engineering teams have developed a full-scale agent-based model to simulate the health care system in a city because of the complexity of the parameters and agent specifications. BOHC's model of Boston's health care system is the first of its kind and the team made sure to use detailed documentation methods if another team of systems engineers wanted to continue working on the model or use agent-based modeling to simulate the healthcare system in another city. Additionally, using the AnyLogic software, the BOHC model is completely scalable and can be applied to any city with a change in the parameters' data distributions to represent the new city.

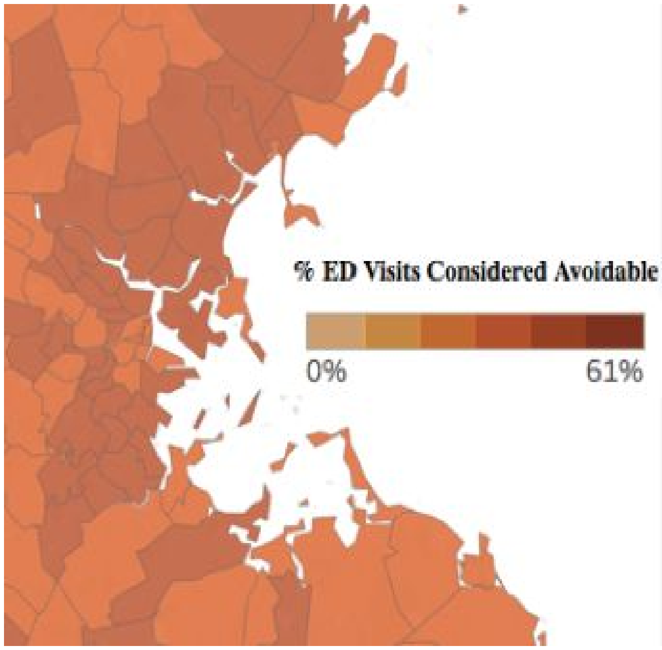
By minimizing the amount of avoidable visits to the emergency department and keeping the target demographics out of the healthcare system cycle, there is substantial potential to enact meaningful change and reduce costs incurred by both public and private sector healthcare institutions.

In terms of valuable lessons learned, the team has improved its knowledge of agent-based modeling significantly. The team has also become more adept with model formulation by first creating a theoretical model output, and then translating this into coding. The team has also learned extremely valuable skills in terms of working effectively within a team, managing team members and holding each other accountable for strict expectations and deadlines. As all five of BOHC's team members plan on pursuing an advanced degree or entering the workforce next year, team dynamic and management skills will be critual. The entire team will continue to hone and development the management skills that we learned while completing this project.

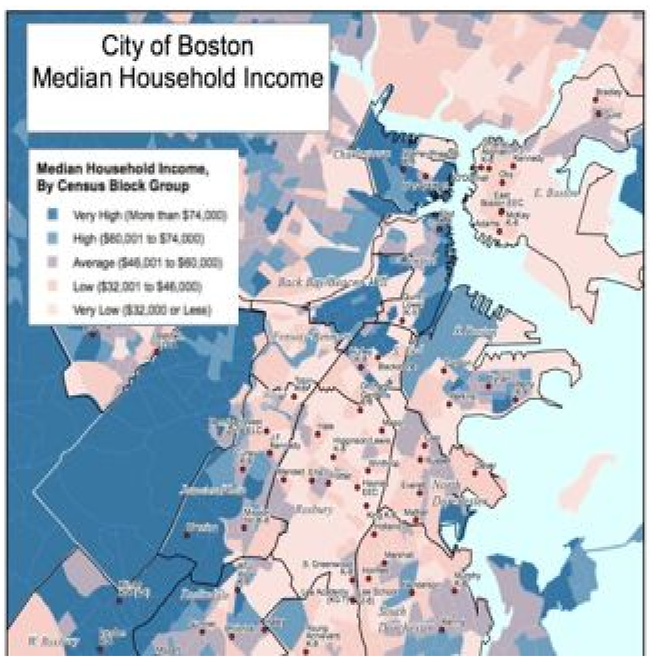
XVI. Appendices

Appendix 1

Map of Percentage of Emergency Department Visits Considered Avoidable by Zip Code in Boston Metro Area



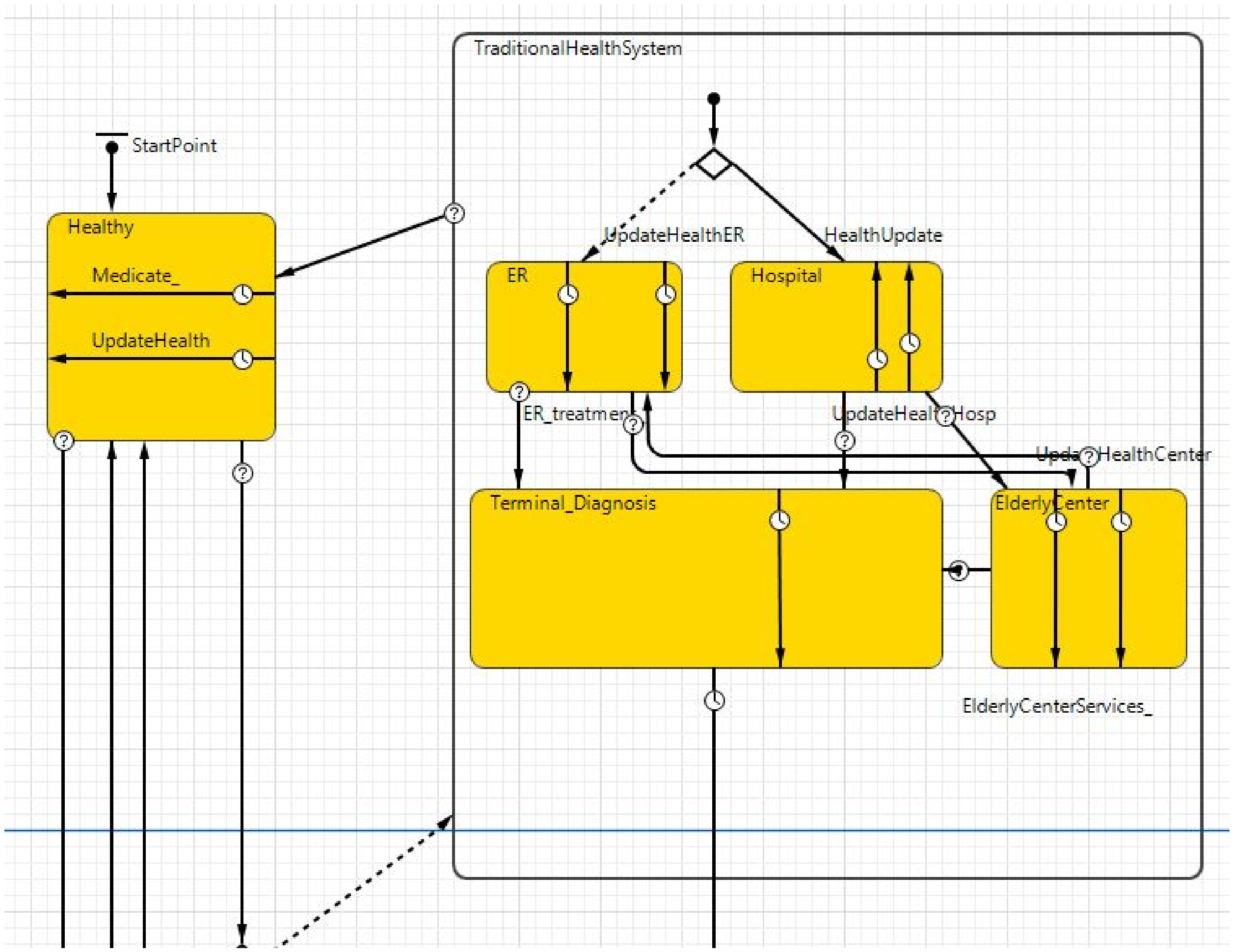
Map of Median Household Income by Block in City of Boston



Lightest: <$20K
Dakest: >$74K

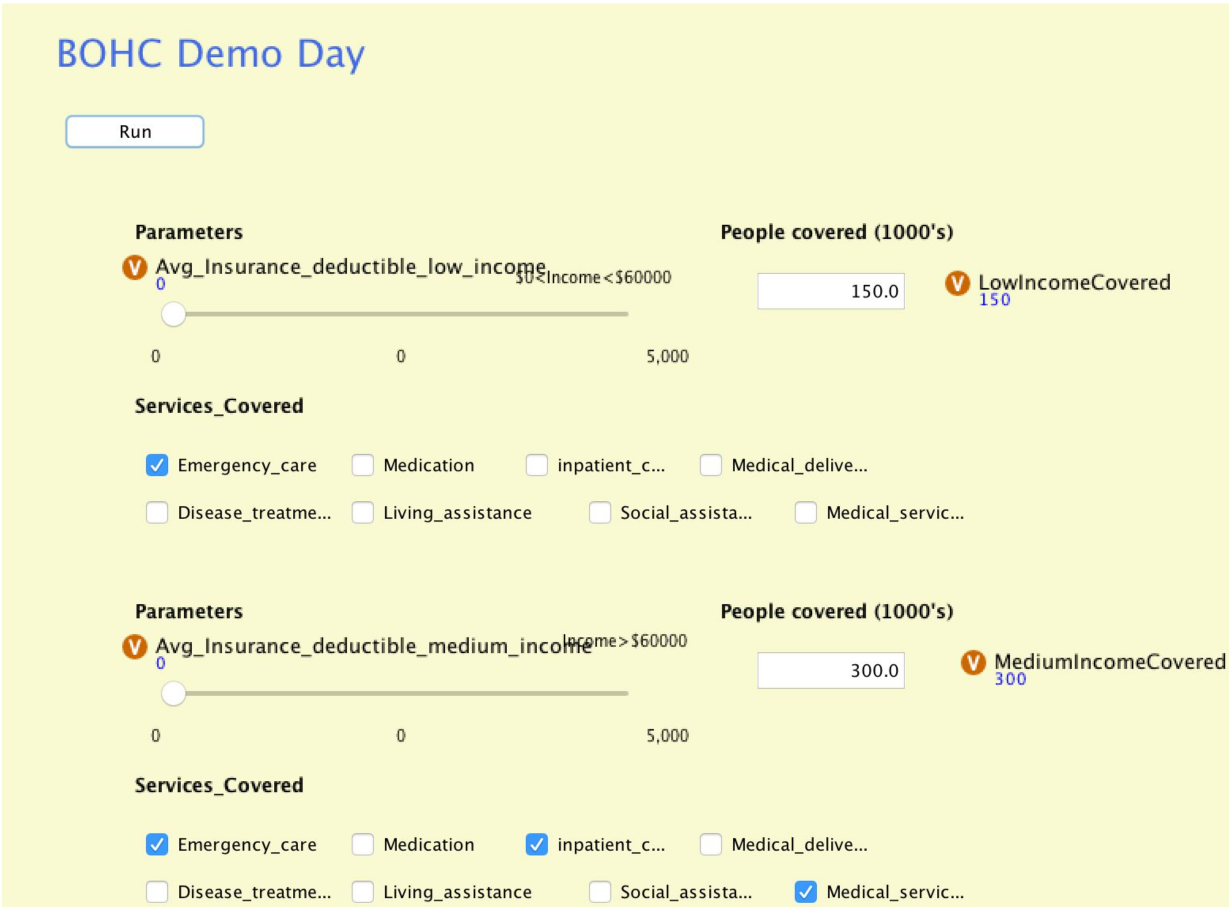
Appendix 2

Detailed AnyLogic Statechart for Individual Model Decisions



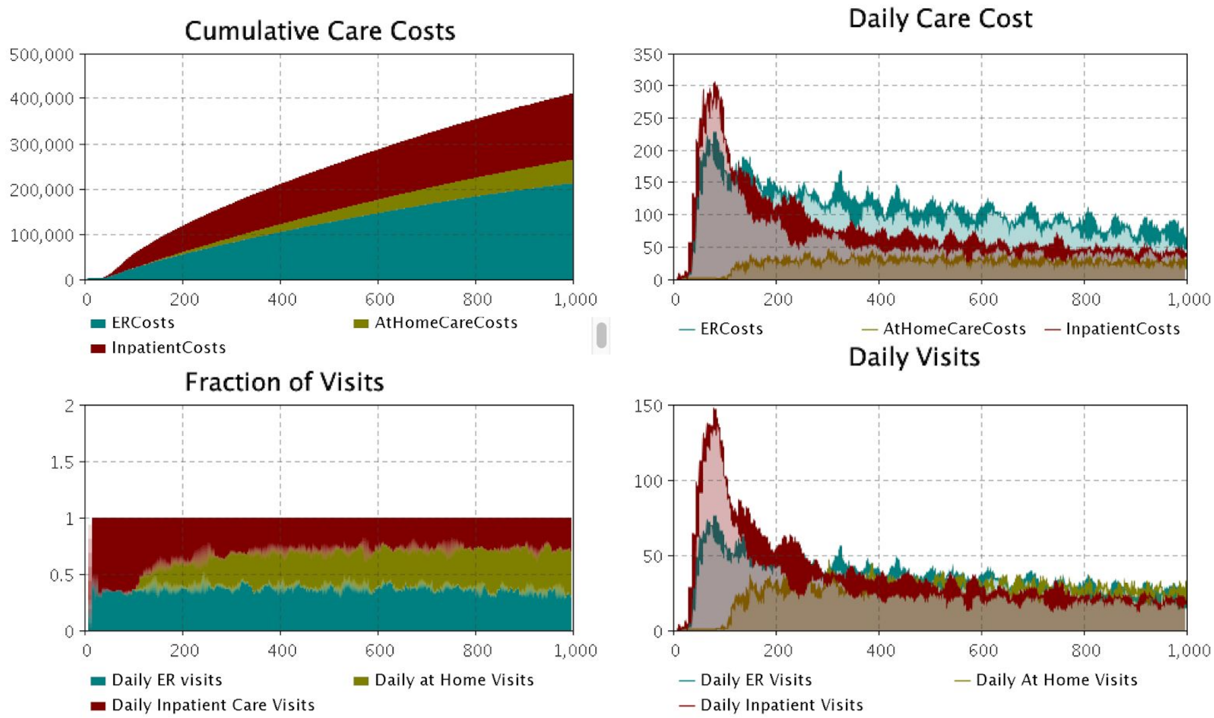
Appendix 3

User Interface and Dashboard



Appendix 4

Output of Example Policy Change (Results from Model)



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