LEVERAGING AI AND SUPPLY CHAIN TECHNOLOGIES WITH THERMAL IMAGING AND TELEMEDICINE FOR EARLY DETECTION AND PREVENTION OF COVID-19 AND RESPIRATORY INFECTIONS IN URM COMMUNITIES

By

Gohar Azeem

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ABSTRACT

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Gohar Azeem, PhD

The University of Texas at Arlington, 2022

Supervising Professor: Erick C. Jones

The underserved population could be at risk during the times of crisis, unless there is strong involvement from government agencies such as local and state Health departments and federal Center for Disease Control (CDC). The COVID-19 pandemic was a crisis of different proportion, creating a different type of burden on government agencies. Vulnerable communities including the elderly populations and communities of color have been especially hard hit by this pandemic. This forced these agencies to change their strategies and supply chains to support all populations receiving therapeutics. The National Science Foundation (NSF Award # 2028612) funded this research to help federal agencies with strategies. This research is based on a NSF funded grant to help federal agencies with strategies by investigating supply chain strategies that would minimize the impact on underserved populations during pandemic and by integrating artificial intelligence and social determinants of health to make optimized supply chain models more robust and updated real-time. This project leverages Artificial Intelligence (AI) integrated with an Infrared Facial Recognition, Thermal Imaging and

Telemedicine tools to improve patient outcomes for those most at-risk (URM Community) for SARS-CoV-2 (COVID-19) and other severe respiratory illnesses, how this information can be used to design supply chain model that ensures that vaccines can be delivered to this community to prevent and minimize the impacts of COVID-19. The specific objectives of this study were;

1) Use convergent innovation ecosystems and platforms [2] to identify Automated Data Capture (ADC) and Artificial Intelligence (AI) needed to automate the healthcare supply chain.

2) Model the COVID-19 Supply Chain from manufacture to vaccine delivery that optimizes the most efficient manner to impact the most at risk populations and communities; and

3) Identify the readiness and the societal cost benefit of this model for use when as vaccines become ready for use.

The outputs of optimized supply chain model using different scenarios showed the prioritized distribution of COVID-19 vaccines to at-risk communities with much higher service levels as compared to non-prioritized communities and overall service levels. This study also identified the phenomena of last mile importance, which is missing in existing healthcare supply chain models. The last mile transportation concept was critical in saving lives during the pandemic for underserved populations. The supply chain model then maximizes social goods by sending drugs or vaccines to the communities that need it the most regardless of ability to pay. The outcome of this study helped us prioritize the communities that need the vaccines the most. This informs our supply chain model to shift resources to these areas showing the value in real time prioritization of the COVID-19 supply chain. This research provides information can be used in our healthcare supply chain model to ensure timely delivery of vaccines and supplies to COVID-19 patients that are the most vulnerable and hence the overall impact of COVID-19 can be minimized.

Table of Contents

Table of Figures

List of Tables

Chapter 1: Introduction

1 Chapter 1: Introduction

1.1 Overview

The understanding of supply chain and transportation in recent times has brought life and death to underserved communities in the US and other countries like India, UK, etc. The COVID-19 pandemic was a crisis of different proportion, creating a different type of burden on government agencies. The COVID-19 pandemic has severely affected the entire world with more than 464 million cases and over 6 million deaths worldwide (John Hopkins). The US is one of those countries, which has suffered the most from this disease with above 79 Million confirmed cases and approximately 968,521 deaths as of March 17, 2022. The underserved population could be at risk during the times of crisis, unless there is strong involvement from government agencies such as local and state Health departments and federal Center for Disease Control (CDC). The COVID-19 pandemic was a crisis of different proportion, creating a different type of burden on government agencies. Vulnerable communities including the elderly populations and communities of color have been especially hard hit by this pandemic. This forced these agencies to change their strategies and supply chains to support all populations receiving therapeutics. This proposed study will help federal agencies with strategies by investigating supply chain strategies that would minimize the impact on underserved populations during pandemic and by integrating artificial intelligence and social determinants of health to make optimized supply chain models more robust and updated real-time. This project seeks to leverages Artificial Intelligence (AI) and automated data capture tools to improve patient outcomes for those most at-risk (URM Community) for SARS-CoV-2 (COVID-19) and other severe illnesses, how this information can be used to design supply chain model that ensures that vaccines can be delivered to this community to prevent and minimize the impacts of COVID-19. This study will also explore the phenomena of last mile importance, which is missing in existing healthcare supply chain models. The last mile transportation concept is critical in saving lives during the pandemic for underserved populations. The supply chain model then maximizes social goods by sending drugs or vaccines to the communities that need it the most regardless of ability to pay. The outcome of this study will help us prioritize the communities that need the vaccines the most. This informs our supply chain model to shift resources to these areas showing the value in real time prioritization of the COVID-19 supply chain. This study will provide information, that can be used in our healthcare supply chain model to ensure timely delivery of vaccines and supplies to COVID-19 patients that are the most vulnerable and hence the overall impact of COVID-19 can be minimized.

While this pandemic has affected the people of all races and origins, the African American and other communities of color have been specifically affected by the coronavirus pandemic (Dorn et al. 2020). According to a study about COVID-19 exacerbating inequalities in the US, the total number of deaths due to COVID-19 are disproportionately high among the African American communities as compared to the overall population in the US. (Dorn et al. 2020). Another study was conducted to assess differential impacts of COVID-19 on black communities (Millet et. al 2020). The outcome of their study shows that counties that have highly black population are more susceptible to contracting the COVID-19 virus. After accounting for county-level factors such as age, poverty, epidemic duration and comorbidities, death due to coronavirus was significantly higher in black rural and small metro counties (Millet et. al 2020). According to the Office of Behavioral Health Equity (OBHE 2020), the coronavirus pandemic has exposed the deep-rooted disparity in the health care setup towards the underserved communities and aggravated the socio-economic factors that contribute to poor health outcomes. Racial and ethnic minority groups are experiencing higher rates of COVID-19 infection, hospitalization, and death. Inequities in the social determinants of health have historically prevented these groups from having the same opportunities for economic, physical, and emotional health. These inequities are highlighted by the factors that contribute to increased risk of COVID-19 exposure, severe illness from COVID-19, death, and unintended consequences of COVID-19 mitigation strategies. (CDC 2020).

While the vaccines have already been developed for COVID-19, the big challenge is how to get these important medicines to the communities that are most at risk, especially in the underrepresented minority (URM) community. This challenge becomes more significant due to health disparities for underserved communities. An innovative and robust pandemic vaccine supply chain needs to be designed and developed to tackle the daunting task of mass vaccination under stringent operating constraints. Pandemics such as the coronavirus disease (hereafter COVID-19) exert severe pressure on healthcare systems, which in turn affects timely delivery and distribution of vaccines to healthcare centers. Most governments are responding to this distribution challenge by building or upgrading healthcare infrastructure to enhance geographic accessibility of health services. Nevertheless, it is equally important to design an optimal vaccine supply chain that supports an effective, agile, and responsive distribution network to maximize geographic coverage of populations at greater risk while keeping distribution lean. Evidence-based decision-making to help optimize and allocate vaccines in a timely manner is critical to protect lives during the COVID-19 pandemic. Health organizations are calling for novel approaches and methods to optimize immunization supply chains and meet the demands of an increasingly large and costly portfolio of vaccines (WHO 2020).

Different vaccines have been created in order to help reduce the spread of the virus (Calina 2020). Government agencies ordered a lockdown to be put into place with social distancing and the use of wearing masks in order to control the COVID-19 pandemic. For long-term purposes, it is necessary to make sure that the vaccines are distributed evenly between the populations [12]. Given the complexity of global vaccine supply chains and the constraints related to supply, demand, and capacity, various distribution scenarios should be formulated to help optimize the system for acquiring, prioritizing, and distributing vaccines to the populace (Uscher-Pines et. al 2006 and Medlock et. al 2009). Few studies have been developed for an effective distribution for vaccines to make certain that the vaccines are delivered in an effective manner to the people who are in need the most (Medlock et. al 2009 and Lee et. al 2012). These studies did not fully take into consideration the constraints which affect a vaccine supply chain which can be optimized to mitigate the risk of the infection. As a result, a robust model is needed to conceptualize the process of the downstream vaccine supply chain in order to ensure efficient distribution of the vaccines.

The process of the distribution of the COVID-19 vaccines is a complex task. The last mile transportation concept is critical in saving lives during the pandemic for underserved populations. The focus of this research on optimizing COVID-19 therapeutics supply chain to get these lifesaving therapeutics to the communities that are most at risk, especially the underserved communities. This becomes more significant due to health disparities for underserved communities. This National Science Foundation funded study (Award Abstract # 2028612) identified the phenomena of last mile importance and its criticality in saving lives during the pandemic for underserved populations. The research which has been performed previously has not incorporated the factors and constraints which affect a vaccine supply chain which can be optimized to reduce the risk of the infection. We have defined community health index as a way to identify those communities, which are most vulnerable to COVID-19 and using this in our MIP supply chain model to prioritize highly vulnerable communities with higher service levels to ensure the timely availability of therapeutics to these underserved community. This research develops a mathematical model to support vaccine allocation decisions based on exposure risk, and operational constraints including capacity of medical centers, vaccine stocks, and routes optimization. Using the city of Houston, Texas, the 4th largest city in US as a case study, we applied the proposed model to test different scenarios of vaccine allocation and distribution with different priority levels. In this study we assume that the vaccine is already manufactured and available in the market for distribution and that limited supply and excessive demand necessitate optimizing the allocation of vaccine by prioritizing people with higher risk of infection and greater probability of social contact with others; and that the vaccine is to be administered at state-run medical centers.

Our optimized healthcare supply chain and enhance Telemedicine Tools to have the greatest impact on improving health outcomes by early detection of illness in those most at-risk, vulnerable populations. Our model provides vulnerable population with convenient way to communicate with health providers when the healthcare is ready accessible in the home or nursing facility. We collaborated with the City of Houston Health Department (HHD) to capture the data needed to model a community that has these challenges. The HHD is currently working with the hospital districts, the veterans' administration, and neighborhood centers to create models to determine the capacity (e.g., how many beds, nurses and social workers) needed for these communities. We created a COVID-19 healthcare supply chain model that can leverage the use of data capture technologies that already exist at some of these facilities. The ability of real-time data capture, robust optimization engines, and artificial intelligence represent a revolution in AI application to improve health disparities and healthcare delivery. Given the nature of the current crisis, the investigation and the development of a robust AI based Healthcare Supply Chain for COVID-19 medicinal delivery to underserved populations must happen quickly. We worked with the HHD, nurses, and social workers to understand, investigate, and developed a supply chain model that can be deployed immediately.

1.2 Research Question and Hypothesis

As Vaccines are already developed and approved to combat COVID-19, we have witnessed that there was a big challenge on delivery of vaccines to the populations and to be more focused on the supply chain to get the vaccines from the labs and manufacturers to the elderly and underserved, and with new variants and need for booster shot, immediate attention is required to tackle these challenges not only for COVID-19, but also for future pandemics of similar nature. Innovation and technology such as Artificial Intelligence will be needed to take advantage of the newest automatic data capture technologies that model ever-changing conditions to provide service to underserved populations. ***Developing the means and technologies to deliver the vaccines to this population is the operations engineering aspects that are necessary to ensure vaccine security*** (fake vaccines to the poor), shortages (drugs given to the rich; running out for underserved populations), and in-home monitoring system that minimize risks and exposures to the patient, the nurse, and social worker.

1.3 Hypothesis Testing:

Pill Confirmation:

H_0: The "Pill Consumption Confirmation" Telemedicine model will accurately verify pill confirmation process with accuracy of above 70%.

H_1: The "Pill Consumption Confirmation" Telemedicine model will not accurately verify pill confirmation process with accuracy of less than 70%.

Sickness Detection:

H_0: The AI enabled model will accurately detect sickness through thermal imaging and facial recognition with accuracy of above 70%

H_1: The AI enabled model will not accurately detect sickness through thermal imaging and facial recognition with accuracy of less than 70%

Supply Chain (Service Levels):

H_0: The Prioritized Supply Chain distribution model to underserved communities will results in higher service levels and equal cost as compared to equal distribution model.

H_1: The Prioritized Supply Chain distribution model to underserved communities will not results in higher service levels as compared to equal distribution model.

Supply Chain (Cost Analysis):

H_0: The Prioritized Supply Chain distribution model to underserved communities will results in significantly higher overall cost as compared to equal distribution model.

H_1: The Prioritized Supply Chain distribution model to underserved communities will not results in significantly higher overall cost as compared to equal distribution model.

1.4 Research Goal and Objectives

Our **research goal is to investigate a Healthcare Supply Chain Model that leverages AI and Telemedicine for Early Detection and Prevention of COVID-19 and Respiratory Infections in URM communities by provide timely delivery of vaccines to COVID-19 patients that are most at risk for severe illness, defined as hospitalization, ICU admission, mechanical ventilation, or death.** We target the neighborhoods with underserved and underrepresented minority communities (UMCs) that are served by the HHD.

Our specific objectives are to:

1) *Use convergent innovation ecosystems and platforms to identify Automated Data Capture (ADC) and Artificial Intelligence (AI) needed to automate the healthcare supply chain. This includes Integrate AI with facial recognition and thermal imaging as a noncontact method to monitor fever, and potentially detect the progression and onset of respiratory illness, requiring medical intervention.*

2) *Model the COVID-19 Supply Chain from manufacture to vaccine delivery that optimizes the most efficient manner to impact the most at risk populations and communities; and*

3) *Identify the readiness and the societal cost benefit of this model for use when as vaccines become ready for use.*

1.5 Research Approach

We will investigate the following objectives:

Specific Objective 1: Identify the Automated Data Capture and Develop the Artificial Intelligence (AI) Algorithms needed to automate the COVID-19 Healthcare vaccine Supply Chain Nodes

Internet of thing and automatic data capture technologies

Our model includes integrating Facial Recognition Technology (FRT), Automated Data Capture (ADC), and Artificial Intelligence (AI) with Deep Learning (DL), Machine Learning (ML) and natural language processing data from sensors and databases [8]. Data collected and processed will provide meaningful health insights quickly and accurately to improve diagnosis and treatment. Our model improves timely delivery of medication or other medical therapeutics, and to monitor those that remain unvaccinated and most at-risk for disease. While this model focuses on COVID, it can be used to increase early detection of other respiratory diseases and illnesses that may be indicated by fever or monitoring vital signs remotely.

Early identification of minimally symptomatic (paucisymptomatic) or asymptomatic phases of COVID-19 and prompt response to infected cases is crucial. AI and machine learning (ML) can help determine infected patients who are more likely to suffer more severely from COVID-19 and quickly provide more accurate patient risk scores that will help decide when urgent treatment (and resources) is needed [7]. ML evaluation of complex underlying relationships between clinical variables in COVID-19 useful for the development of a computational diagnostic test based on signs, symptoms, and laboratory results, these correlations can also yield critical insights into the biological mechanisms of COVID-19 transmission and infection [9].

We hope to distinguish COVID-19 from seasonal influenza and confirm with testing.

Eligibility criteria and participant recruitment plan, the target population,

- Elderly population -Residents of nursing homes, age 60 - 90 yrs. with no physical limitations or reduced mental capacity that would make patient unable to be screened for the study.

A maximum of 60 participants will be selected from each cohort for this pilot study.

The elderly vulnerable population will be drawn from residents of private nursing homes and assisted living facilities in the Greater New Orleans area and those HHD's elderly care division provides care between the services facilities, the hospitals and homecare. In Houston, HHD has the responsibility for community health, particularly for the underserved population that might not have commercial insurance plans (Medicaid and Medicare). HHD categorizes the epidemic zones as the medical clinics that diagnose and treat patients for contagious diseases. All nursing home residents are eligible unless physician determines health status is physically or mentally incapacitated, as determined by the Nursing Home physician.

All cohorts will be selected for using the Social Vulnerability Index (SVI) which identifies communities as at-risk and maps neighborhoods based on potential negative effects on communities caused by external stresses on human health such as socioeconomic and environmental factors, lack of access to transportation or nutritious food [13]. The communities are points of interest and our AI healthcare supply chain model. All participants will be selected from underserved minority communities, who may have medical comorbidities resulting in an increased risk of severe COVID-19 outcomes and more likely to be vaccine hesitant or vaccine refusal due to lack of trust in the medical community.

In order for AI to support the public health decisions we will utilize the partnership with HDHHS to keep track of those who are highly susceptible to the virus, those who are infected by the virus, and the location of their treatment especially those staying at home. We seek to utilize AI to provide additional tracking of those receiving treatment and understanding the outcomes for cases at home and at the hospital. We will seek to have the models provide feedback on how the point of care shifts from the hospital setting to the home. Our additional expected outcomes for the AI component are to provide insights on how to address both the community and the individual patient needs. It also can serve to inform on what can be collected autonomously to help address not only the individual wellness but the overall wellness of underserved communities. We expect as an additional outcome that the models will simulate case studies for locations where COVID-19 is prevalent or not and the best practices that can be disseminated throughout Texas and other related US communities.

Specific Objective 2: We seek to model the COVID-19 Vaccine Supply Chain from manufacture to home delivery that optimizes the most efficient manner to impact the most at-risk populations

We are expecting to build off our previous research and parameters the previous multi-objective supply chain optimization models with AI Formatted Data. We expected stochastic Markov Decision Process [MDP] with Q Learning for the modeling. We will re-define the models with conventional nodes such as drug manufacturer, warehouse and distribution centers, and stores with nodes such as pharmaceutical public private partnership re-testing repackaging center, hospital, service centers and home and nursing home locations. Supply Chain channels such as direct ship from manufacturer to home customer will be considered for ensuring that the underserved at risk populations receive priority on receiving drugs, ventilators, and protective masks for their healthcare provider.

Specific Objective 3: We seek to identify the readiness and societal cost benefit of this model for use when medications become ready for the COVID-19 outbreak

Finally we expect to develop a framework for developing COVID-19 Multi-Objective Supply Chain Optimization models that ensure that at risk patients receive the necessary vaccines to minimize the spread of the disease and support quality of life. The COVID-19 models will seek to minimize the tradeoff between optimizing profit and minimizing the cost of life. Consideration action and rewards through a Markov Decision processes as a key to the some of the models. We expect to understand performance of the models (actions) with expert validation provided by the HDHHS faculty and staff that include infectious disease MDs, epidemiologist, and elderly care healthcare professionals. We expect a feedback loop created by the automatic data capture and AI middle layer that allows for the ever changing conditions of the COVID-19 supply chain.

Chapter 2: Background/Literature Review

2 Chapter 2: Background

An effective distribution of the vaccines is key for the risk mitigation of the community during a pandemic. A standard vaccine supply chain consists of the following: manufacture, packaging, storage, domestic and global distribution, cost-effective, and uninterrupted supply of vaccines to the population (U.S. Department of Health and Human Services 2005). The difference between a standard vaccine supply chain and a pandemic vaccine is that, previously healthcare and other vaccine providers were to purchase vaccines directly from the manufacturers. For government agencies, they are more susceptible to buy the vaccines directly from the manufacturer in order to ensure an early vaccination delivery. Government agencies are then able to distribute the vaccines to health centers after the vaccines are procured. During pandemic vaccine supply chain, the healthcare providers register their interest with public health programs rather than with supply chain vendors (U.S. Department of Health and Human Services 2005). Brown et al. 2014 hypothesized a typical vaccine supply chain as a four-level delivery system that incorporates the departmental stores, and one regional store.

2.1 <u>COVID-19 Pandemic and the Healthcare Crisis</u>

The SARS-COV-2 the deadliest RNA virus and pandemic in history, with over 45,235,796 cases and 731,000 deaths in the US as of October 2021 [3] To date the FDA issued Emergency Use Authorizations (EUA) for three COVID-19 vaccines available for ages 12+ with 77.2% vaccinated with at least one vaccine shot, and only 57.3% fully vaccinated. Merck has submitted an antiviral medication to the FDA for approval and there are other vaccines and medication candidates in clinical trials. Vaccine boosters have been approved for those over 65, immunodeficient and high-risk individuals and vaccines are being reviewed for use in children 5-12 years old [3].

The US hoping to reach herd-immunity across all populations before COVID-variants emerge with higher mortality rates or that evade current vaccines, making them ineffective. Vaccine administration sites extended beyond hospitals and healthcare facilities, to pharmacies, businesses partnerships, popup drive through vaccination sites, and utilize community centers and sports arenas in an effort facilitate access expedite the vaccination to get 70-80% of the population fully vaccinated. Efforts to increase vaccination rates for those over 18 years old, include Federal and employer mandates to shift more from vaccine-hesitant or vaccine-refusal to vaccine acceptance.

During period of high incidence rate, hospital systems were overwhelmed, straining their capacity to provide routine and emergent medical care especially in communities of vaccine-hesitancy or vaccine-refusal. Due to the overburdened hospitals and providers and fear of exposure to COVID in clinical settings, many hospitals and patients, even those with life-threatening diseases, postponed routine medical checkups and elective surgeries [4].

We propose adoption of advanced digital technology tools for surveillance, prediction, and diagnosis to fight the COVID-19 pandemic. When face-to-face patient visits were limited, telemedicine or telehealth tools are increasingly implemented to continue patient care, follow up, treatment and anticipating the patients who are more likely to get severe disease. (AI)–powered diagnostic tools, voice-interface systems, and mobile sensors such as smart watches, oxygen monitors, or thermometers have been added to enhance telemedicine [5] [6].

The Drug Supply Chain Security Act (DSCSA) modified the drug e-pedigree language in January 2015 to provide uniform national standards for wholesale distribution of prescription drugs, tracing lot level transactions from manufacturer to pharmacies. The DSCSA helps protect patients from receiving harmful counterfeit or other illegitimate drugs. This pharmaceutical supply chain identification enables AI integration allows telemedicine visit real-time monitoring of patient compliance. The capability reduces medication administration errors and improper dosing, which disproportionately affects the elderly. In the context of controlling chronic illnesses and communicable diseases like COVID pandemic, the ability to track COVID test kits and specimens combined with contactless surveillance methods are of particular importance. AI and machine learning (ML) can play a crucial role in ensuring policies, management and resource allocation like testing kits more efficient and improve our response to this crisis [7]. In addition, the FDA is working with drug manufacturers, developers, and researchers to help expedite the development and availability of additional vaccines, and medical therapeutics, COVID-19 antibodies, and medicines to prevent or treat COVID-19. Tracking vaccines, doses, and the flow of vaccines and medicines through the supply chain during this crisis, ensuring safe and timely delivery to the sites of vaccination is a complex task. This is complicated by the influx of fraudulent COVID-19 diagnostic, prevention, and treatment claims, making supply chain tracking paramount to keep public confidence in the healthcare system.

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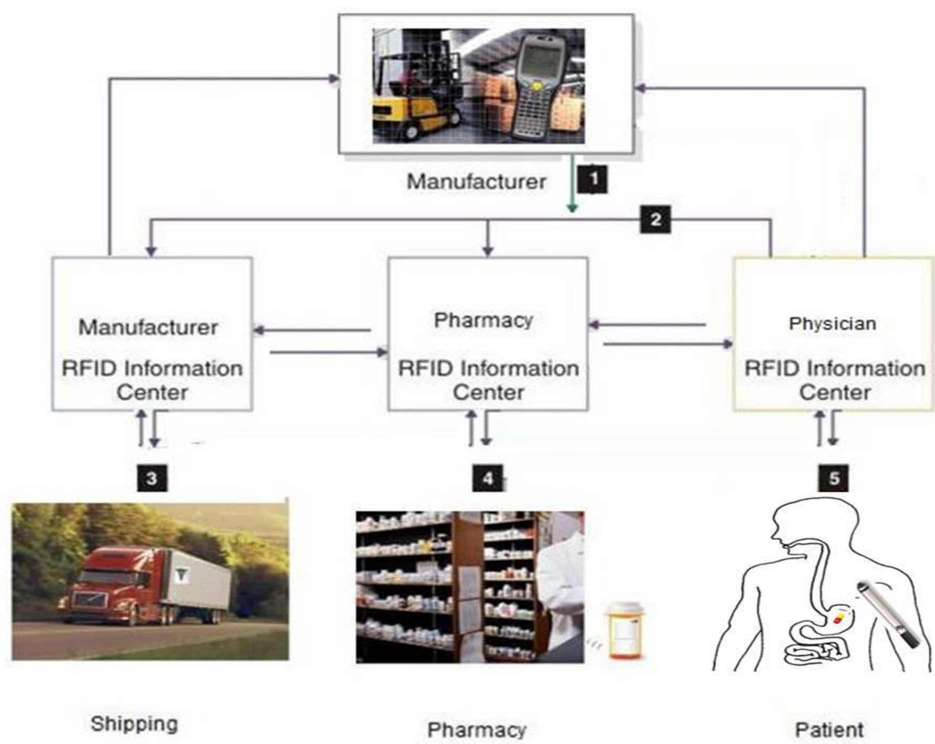


Figure 2-1: Revised from (Jones 2009 [1]) the COVID-19 Healthcare SC

Jones (2009) [1]published a study that describes tracking the life of medications from the point of manufacture to ingestion utilizing upcoming FDA standards such as the E-pedigree (Electronic Pedigree) proposed standard. E-pedigree is an electronic document that specifies information about the purchase of a drug, dispensing the drug to hospitals, and administering the drug to the patient. A system capable of tracking patients, all of their medications, and their prescription compliance would also eliminate errors in medication administration, improper dosages, and adverse reactions to pharmaceuticals, which disproportionately affect the aging population. He theorizes that a wireless system capable of measuring and reporting physiologic data will not only facilitate current monitoring systems and data collection but may also create real-time methods to assess therapy and control chronic illnesses and communicable diseases (Jones, 2009) [1].

(Brandeau et al. 2005) showed that the optimum resource allocation depends on population size, the status of the pandemic on a local level, precautionary measures such as wearing masks, and the transmission rate of the infection. The demand and capacity to distribute the vaccines to the population, as needed, is an important parameter in the distribution model. There are, however, unpredictable emergency situations which will cause challenges when executing strategies to resolve the vaccine decision issues. (Arora et al. 2010) used a cost-benefit-based model to optimize aid during public health emergencies. The key results of the research consisted of the following; a higher flexibility is to be accomplished by postponing on the decision of how to pre-allocate; smaller counties benefit more from mutual help, and lastly, in order for significant savings, groups should be prioritized in allotting the vaccines.

In the development of an optimum COVID-19 vaccine supply, it is determined by the constraints imposed by the vaccination context. Approximately 5.6 billion individuals in the world need to be vaccinated, meaning that there needs to be a mass production in a short period of time. Vaccine supply is delayed by the capacity of the method of delivery and the capacity of health care centers to vaccinate the individuals within the time period.

In the following sub-sections, previous literature on the communities that are disproportionately affected by the pandemic, vaccine supply chains and pandemic supply chains is presented and explored.

2.3 The most at Risk Populations

COVID-19 pandemic has caused disproportionately effects on vulnerable populations, people of color or those with pre- existing health conditions. The elderly and underserved communities are particularly at most risk. 80% deaths reported in the U.S. have been in adults 65 years old and older [28]. As seen in figure 2, the percentage of COVID-19 deaths reported are far higher in elderly population of color as compared to others. The same fact is also reflected in table 1 which shows the count and percent distribution of deaths involving COVID-19 with distribution of weighted and unweighted percent population by race and time period.

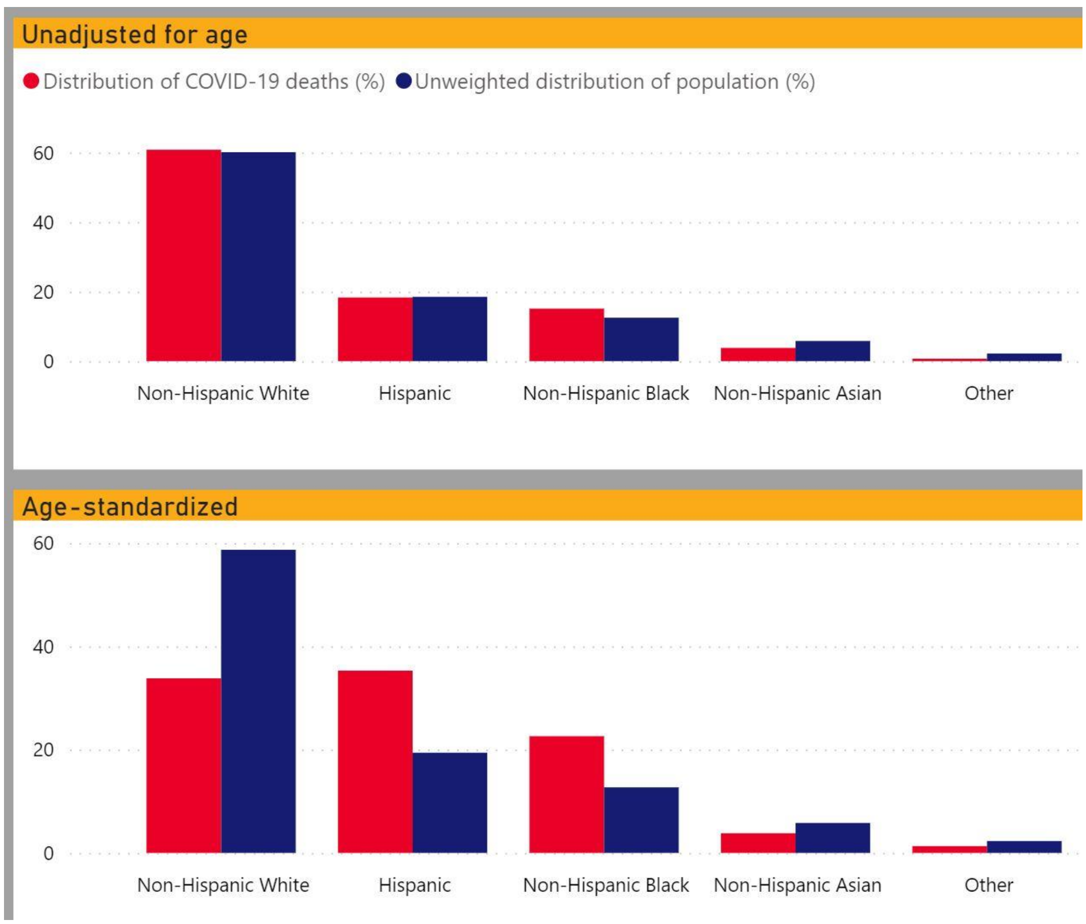


Figure 2-2 Crude and age-adjusted percent of COVID-19 deaths and unweighted population distribution by race (CDC 2020)

A study of selected states and cities with data on COVID-19 deaths by race and ethnicity showed that 34% of deaths were among non-Hispanic Black people, though this group accounts for only 12% of the total U.S. population (Holmes et. al. 2020). In Chicago, residents in highly segregated neighborhoods with higher social vulnerability, such as higher levels of poverty and lower levels of education, income, and employment, are disproportionately exposed to social and health risks. This intersection of factors was found to be associated with high death rates from COVID-19 (SJ et. al 2020).

Similarly, in a nationwide analysis, counties with higher population percentages of non-Hispanic Black people experienced higher COVID-19 confirmed case and death rates than counties with higher population percentages of non-Hispanic White people (Mahajan et. al 2020).

It is also concerning that a high percentage of Americans do not want to get vaccinated. A study shows that 31.1% of Americans do not intend to pursue being vaccinated when a COVID-19 vaccine becomes available (Callaghan et. al 2020). The likelihood of refusal is higher for Blacks, women, and conservatives, exacerbating existing disparities in COVID-19 outcomes. Blacks were more likely to be hesitant than Whites because of concerns about safety and efficacy, because they lack needed financial resources or health insurance, and because they already had COVID-19 (Callaghan et. al 2020).

Notably, previous research has also shown vaccine hesitancy among Blacks, with evidence that Blacks have refused to participate in HIV/AIDS vaccine trials and are less likely to receive annual influenza vaccinations (US Department of Health and Human Services Office of Minority Health 2018).

Table 2-1 Count and percent distribution of deaths involving COVID-19 with distribution of weighted and unweighted percent population by race and time period (CDC 2020).

Year in which death occurred	Age Group	Non-Hispanic White	Non-Hispanic Black	Non-Hispanic American Indian or Alaska Native [1]	Non-Hispanic Asian [2]	Non-Hispanic Native Hawaiian or Other Pacific Islander	Non-Hispanic More than one race	Hispanic	Unknown [3]
2020/2021	0-4 years	35	30	2	3	2	7	48	4
2020/2021	5-17 years	65	51	5	12	4	2	83	1
2020/2021	18-29 years	704	629	97	93	21	24	1,002	7
2020/2021	30-39 years	1,908	1,777	296	312	58	38	2,960	19
2020/2021	40-49 years	5,486	4,362	539	711	123	119	8,071	46
2020/2021	50-64 years	40,152	21,283	1,873	3,797	389	446	29,597	405
2020/2021	65-74 years	74,064	25,121	1,860	5,631	300	510	28,152	596
2020/2021	75-84 years	111,032	22,396	1,406	6,156	178	504	24,373	563
2020/2021	85 years and over	137,852	16,745	793	6,432	78	375	17,235	374
Total		**371,298**	**92,394**	**6,871**	**23,147**	**1,153**	**2,025**	**111,521**	**2,015**

Any vaccine or treatment should target these high at risk populations first to prevent further loss of life. Therefore, this study looked to identify how socially and medically vulnerable populations overlapped, if and how much they are being underserved in the current testing paradigms, and how to design supply chain for vaccines or drug treatments that prioritizes the vulnerable ensuring they get treatments they need regardless of their income status.

2.4 Vaccine supply chains

The current literature on vaccine supply chain is immeasurable and hypothesized. The majority of the studies were driven by the vaccine effectiveness procurement, distribution and allocation to vaccinate a wider population. (Lee et. al 2011) investigated the impact of a new vaccine on the existing vaccine supply chain with a deterministic mathematical Equation-Based Model (EBM). The results illustrated that the distribution of the newly introduced vaccine needed additional storage and transportation capacity to effectively implement the program of the vaccination. Similarly, by taking into account scheduling preferences of patients and scheduling inconvenience, (Abrahams et. al 2015) argued that the distribution of vaccines presents a number of operations management challenges like, multi-dose vaccine packages, rapid spoilage upon opening, high-cost of wastage, and vaccination needs of patients.

Storage capacity is another factor which impacts the vaccine supply chains. (Shittu et al. 2016) analyzed the influence of variance in supply and demand under scenarios which enhance the supply chain's capability to meet the storage requirements. In Nigeria, a simulation was developed for vaccine storage capacity. The study showed that there was a 55% increase in the storage capacity which was needed to meet the vaccination needs. With the establishment of three more vaccine delivery hubs, there could be a decrease of cold storage requirement of 55% to 33%. The redesign of old vaccine supply chains can therefore be crucial for capacity utilization.

Hospitals and other service providers play a vital role in ensuring that the vaccines are distributed and dispensed effectively. (Lin et al. 2020) created a mathematical model to analyze the decision of the distributor to use a cold chain or non-cold chain to deliver the vaccines. Next, the model was to analyze the influence of a single-step or two-step standard inspection policy of the retailers on the distributor's decision whether to use the cold chain or not. The results represented that the two-step policy, despite being stricter and more costly, was less effective in influencing the distributor to select the cold chain option than the single-step policy was.

2.5 Pandemic vaccine supply chains

In the case of pandemics, vaccine supply chains consist of their own specifics such as, scale, exposure, time-space levels, and constraints. Uscher-Pines et al. 2006 evaluated a sample of 45 national pandemic influenza prioritization plans, including 19 developed and 26 developing countries. It was found that 28 (14 developed and 14 developing countries) out of 45 nations have provided for prioritized vulnerable groups of the population for vaccination. In some countries, higher prioritization of high-risk individuals by healthcare workers and service workers is embedded in the national pandemic vaccination plan (ibid). The study concluded by emphasizing the need to establish priority settings based on individualized modeling or impact estimates to enhance the effectiveness of large-scale vaccination programs to mitigate the risk of community transmission during a pandemic (Uscher-Pines et al. 2006).

Araz et al. 2012 prioritized 15 counties of Arizona based on four distinct H1N1 pandemic vaccine distribution strategies: pro rata distribution; sequential distribution by population size; sequential distribution by estimated periods of pandemic peaks; and reverse sequential distribution by estimated order of pandemic peaks. The study demonstrated that the policies would be effective to reduce the pandemic's impact by optimizing waiting times for vaccines. The results revealed that the two most effective policies for controlling the epidemic and reducing unmet demand are pro rata distribution and prioritization of communities expected to experience the latest outbreak.

Previous research by Huang et al. 2017 and Chen et al. 2020 has investigated risk-based pro rata distribution and prioritization for vaccine allocation in order to reduce the spread of the virus. Medlock and Galvani 2009 used a parametrized model with survey-based contact and mortality data from influenza pandemics to determine optimum vaccine allocation minimizing five outcome measures: deaths, infections, years of life lost, contingent valuation, and economic costs. They found that optimal vaccination is feasible by prioritization of schoolchildren and adults from the ages of 30 to 39 years (Medlock and Galvani 2009). Buccieri and Gaetz 2013 argued that in a pandemic outbreak, priority for vaccination should be given to population groups at high risk and who would experience difficulty reaching health centers, such as homeless people and other disadvantaged groups, to ensure equity and utility. During the H1N1 outbreak in Toronto, the city managed to vaccinate 38 percent of the homeless people via highly accessible community-based vaccine clinics. Taking New York City as a case study, Chen et al. 2020 applied an age-structured simulation model to explore the optimal allocation strategy for the COVID-19 vaccine. They divided the population into seven compartments, and then each compartment was further divided into five age-groups. They analyzed the impact of both static and dynamic policies. The results showed that, when the objective is to minimize deaths, the optimal static approach is to vaccinate the oldest group first and then the younger groups. However, when the target is to mitigate total confirmed cases, then the optimal static policy is to allocate vaccines to younger people even if the supply is scarce. Sudan et. al. 2021 used the concept of Transport Intelligence and Logistics Systems for recovering Supply Chain Disruptions in Post-COVID-19 Pandemic.

In recent years, with an increased focus on renewable energy and the potential reduction of transportation's impact on climate change and other environmental issues, the electric vehicles (EVs) have high importance to address these challenges. Project Drawdown describes electric vehicles as one of the 100 best contemporary solutions for addressing climate change [43]. Even though the emissions from the power plants are used to fuel the vehicles, the electric vehicles will reduce the global air pollution significantly Technologies for EV are increasing which include extending driving ranges and reducing costs [44]. The EVs are not only helping in fighting climate change, but also providing more economical mode of transportation as well. According to a study by Idaho National Laboratory, the breakdown for a gas-powered car vs. an electric car comes out to be $9.83 per 100 miles for a gas car and $5.27 per 100 miles for an electric vehicle. When directly compared, the cost to power an electric vehicle is about half of what it costs to fuel your gas-powered car.

This project aims to create a supply chain model that prioritizes geographic sections in the cities that house vulnerable communities. The study identified the phenomena of last mile importance in achieving the objectives. The last mile transportation concept was critical in saving lives during the pandemic for underserved populations. Integrating the last mile concept along with an accessible healthcare index (CHI) will allow for real-time strategies. The strategies are defined as mathematical models that could be used in real-time for these at-risk communities. The use of electric vehicles (EVs) for last mile transportation will help in reducing carbon emission and fighting climate change.

2.6 Automated Data Capture (ADC) in healthcare

The concept of automated data capture in pharmaceuticals and healthcare is not new. The PI in partnership in HHD published a seminal paper in 2007 [1] which describes an overview of the concept of an all-encompassing automated pharmaceutical tracking system (as seen in Figure 1) that begins with compliance documentation from the drug manufacturer and continues through the confirmation that the elderly or URM patient were reached and presented with an opportunity to be vaccinated or administered a COVID-19 medication or therapeutic, as appropriate. This system also facilitates compliance with Food and Drug Administration proposed e-pedigree requirements and provides data for healthcare decision making. As described earlier this type of approach is key to impacting the underserved populations as medicinals are developed for COVID-19. The real time feedback would be crucial to keeping elderly and underserved patients from having to go to the hospitals and taxing the already overburdened hospitals. This could ultimately increase hospital capacity. Our proposed models would be able to impact the issues of estimating the community needs, understanding vaccine hesitancy, and the timely delivery of COVID-19 medication or other medical therapeutics.

2.7 Artificial Intelligence

Good input metrics are essential for the optimization and implementation of the supply chain. The data collection system which could use IOT or other technologies acquires information from multiple different sources. Each source will provide a metric and observing how those metrics change over time and inform the optimization model is the key novel feature. We will use AI to not only interpret and clean the collected data but also use it to translate a metric into an input variable for the supply chain optimization model. Artificial Intelligence (AI) is just beginning to crack the surface in healthcare. It has the potential to improve diagnosis and treatment, patient engagement and adherence, and administrative applications [5]. AI applications like machine learning and natural language processing can take data from sensors and databases and provide meaningful health insights quickly and accurately. The ability to provide quick and accurate insights allows for quicker and better diagnoses and treatment.

Our model includes integrating Facial Recognition Technology (FRT), Automated Data Capture (ADC), and Artificial Intelligence (AI) with Deep Learning (DL), Machine Learning (ML) and natural language processing data from sensors and databases [8]. Data collected and processed will provide meaningful health insights quickly and accurately to improve diagnosis and treatment. Our model improves timely delivery of medication or other medical therapeutics, and to monitor those that remain unvaccinated and most at-risk for disease. While this model focuses on COVID, it can be used to increase early detection of other respiratory diseases and illnesses that may be indicated by fever or monitoring vital signs remotely.

Early identification of minimally symptomatic (paucisymptomatic) or asymptomatic phases of COVID-19 and prompt response to infected cases is crucial. AI and machine learning (ML) can help determine infected patients who are more likely to suffer more severely from COVID-19 and quickly provide more accurate patient risk scores that will help decide when urgent treatment (and resources) is needed [7]. ML evaluation of complex underlying relationships between clinical variables in COVID-19 useful for the development of a computational diagnostic test based on signs, symptoms, and laboratory results, these correlations can also yield critical insights into the biological mechanisms of COVID-19 transmission and infection [9].

2.7.1 Hierarchical Sparse Learning to Investigate Demographic and Social Factors & Interactions

As we discussed that in this research, we will work on optimized distribution of pandemic vaccine to at-risk communities. In particular, we will introduce social science research to investigate and understand why the URM communities make certain health decisions based on factors from the National Academies of Sciences, Engineering, and Medicine report, Communities in Action: Pathways to Health Equity (2017). At present, there is a knowledge gap to understand structural and social determinants of health given a large number of demographic and social factors. In this research, we will bridge the gap to develop a set of data-driven analysis tools and machine learning models to offer a deep understanding of health decisions and disparities for URM communities.

To investigate high dimensional data with a large number of factors with complicated interactions, we will develop machine learning methods that care capable of learning high order variable interactions and identify key influencing factors and factor interactions for student study outcomes. Traditionally, the interaction effects are represented as the elementwise product among the variable. For example, the second-order interaction between two variables xi and xj is represented by their elementwise product xi $\odot$ xj. It is noted that in most of the studies of interaction models, only second order or low-order interactions are considered. However, higher-order interactions can be critical and important in many applications, such as the research problems in this project. A major challenge of high-order interaction modeling is the exponentially expanded interaction feature space generated from a large number of interactive factors. For example, when considering the kth-order interactions among a set of variables, the number of interactions is O(dk) with respect to the d variables. Such a large number of interactions make the learning model computationally demanding even when d and k are very small. To tackle this problem, a promising strategy is to exploit sparse structure under this scenario, since only a small subset of the variable and interactions are critical and relevant. Thus, we propose to develop high order structured sparse learning methods to identify important variables and interactions from a high feature space. Moreover, to make an efficient sparse learning framework, we consider the higher-order interaction effects are originated from lower-order ones. Thus, we impose a logical heredity relationship in sparse feature learning. The heredity assumption is that for a variable, if none of its associated kth-order interaction effects contribute to a learning model, then all its associated higher-order interaction effects will also have no effects to the learning model. Based on this heredity structure, we developed a hierarchical sparse model (HSM) that is capable of handling arbitrary-order interactions among features and identifying most important variable and interactions via sparse regularization techniques. The proposed HSM method make it possible to explore complex variable relationships in a potentially extremely high dimensional feature space. Based on HSM, we will construct an interpretable machine learning model to reveal complex variable interactions for college student learning path patterns and their academic achievements. This could overcome the limit of traditional regression models with low order multiplicative interactions. We will employ the proposed HSM model to explore the high dimensional data collected from this project, including various medical, demographic, and social factors. The new knowledge learned from this research will enable us to develop novel and effective strategies to measure, reduce, and mitigate the effects and impacts of discrimination on health outcomes.

2.7.2 Automatic Action Recognition using Deep Learning

Human pose estimation accuracy was greatly improved with the help of convolutional neural networks (CNNs) [6],[7],[8]. However, there is a little research on compact, yet efficient pose estimation methods. A growing number of computer vision and machine learning applications require 2D human pose estimation as an input for their systems. To help the research community boost their work, we have investigated advanced deep learning methods for real-time multi-person system to jointly detect human body, foot, hand, and facial key points on single 2D images. In particular, we explored

OpenPose system which consists of three major blocks: body + foot detection, hand detection [9] and face detection. The core block is the combined body + foot key point detector. It can alternatively use the original body-only models [10]. To achieve automatic data capture, we will extend 2D imaging learning to continuous video stream monitoring and action learning. We will develop human activity recognition system to continuously monitor human activities that can be helpful in surveillance, health care, anomalous behavior detections, personal identity, knowing psychological state, elderly care. The activities can be human to human, independent or human to object interactions and can be monitored using video surveillance, wearable sensors, and human to system interactions.

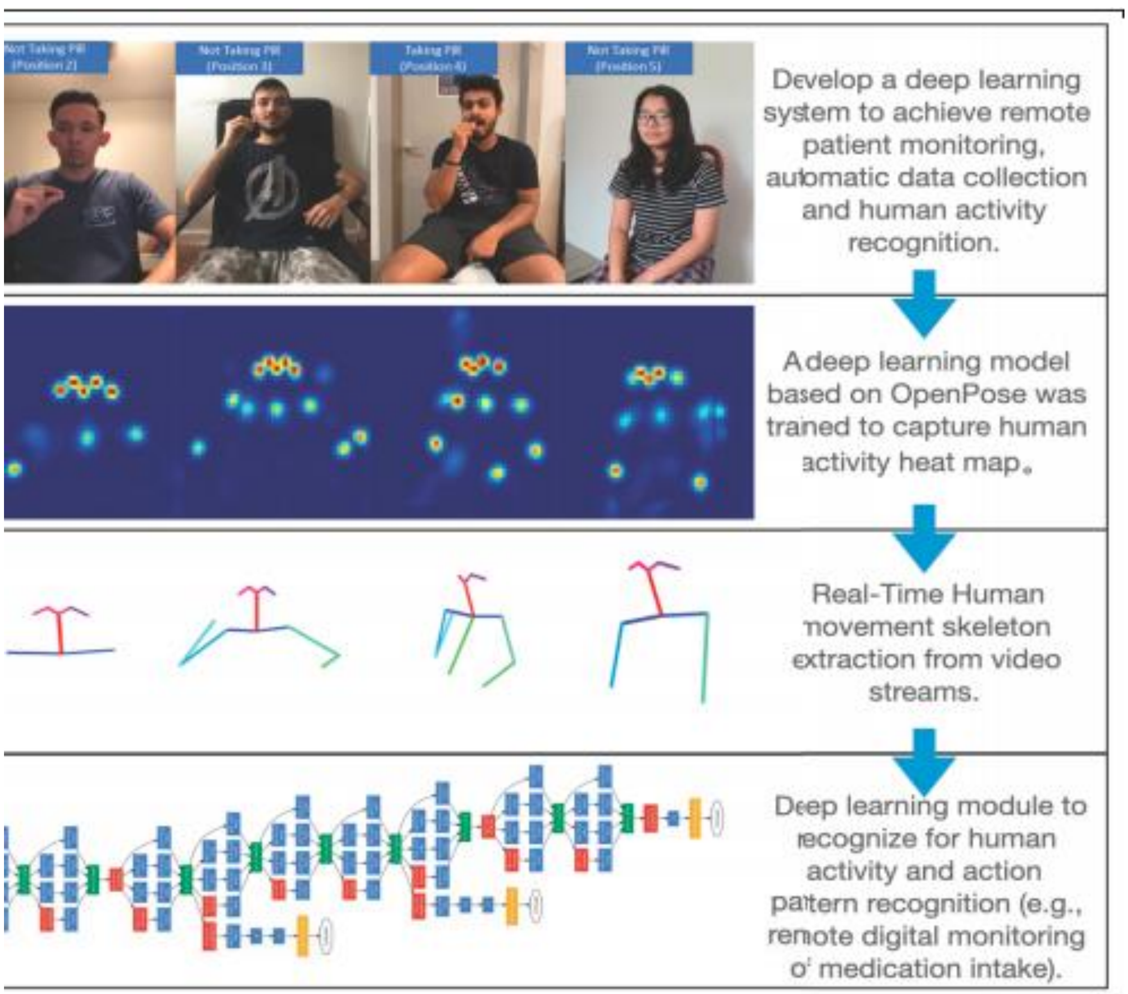
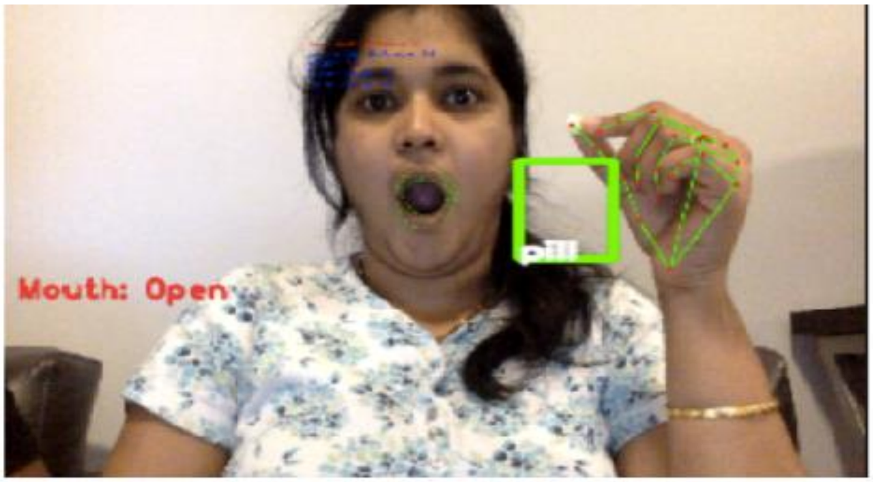


Figure 2-3: Human Activity Recognition System for Automatic Data Collection (Current work in lab)

The human action recognition system developed in this project is used to achieve automatic data collection. It is also a core component of the AI system to provide patient activity monitoring, in-time feedback, and improved medical outcomes.



Pill confirmation model (Current Work)

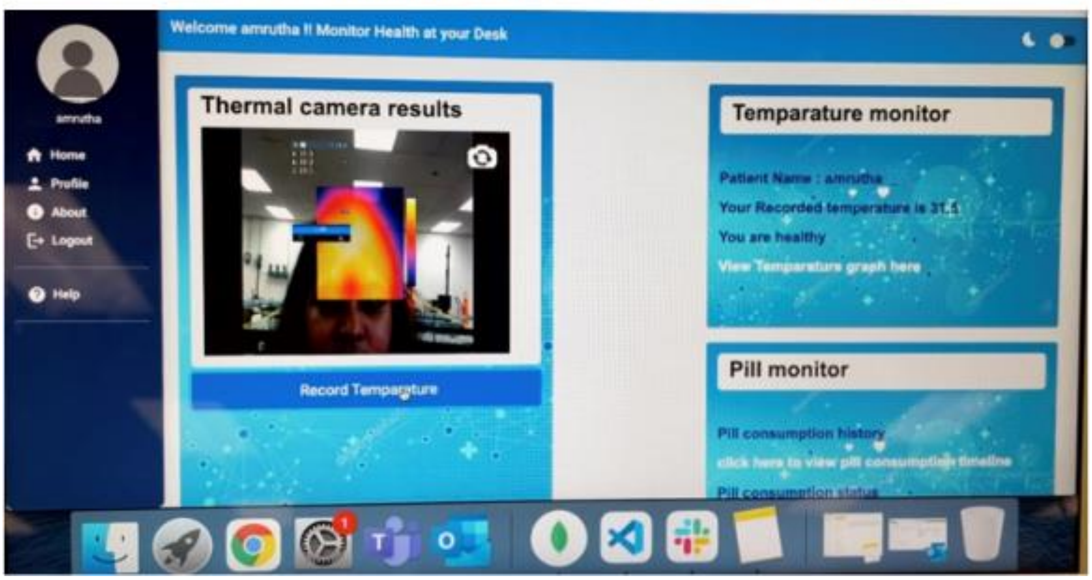


Figure 2-4: Display Output of Pill Confirmation and Sickness Detection Models (Current Work in Lab)

The above figure shows the output of the model. It shows the output for both pill consumption confirmation as well as for thermal imaging and sickness detection.

2.8 Defining the COVID-19 Supply Chain from manufacture to hospital to home care;

Why Current Supply Chains cannot support the COVID-19 Pandemic

While the vaccines are developed and being distributed, the White House and federal administration has expressed their concerns on the supply chain to get the vaccines from the labs and manufacturers to the elderly and underserved especially with race to meet herd immunity before more lethal variants of COVID-19 further complicate our efforts.

The need for supplies for the epidemic is ever changing. The Biden administration is exploring new avenues to reach all communities and administer as many doses of vaccinate as possible across the United States, including engaging local community partners and community- based events. Yet, the final mile of vaccinations will not be met if we fail to change the mindset of those that 25-30% of people in vulnerable populations from probably- or definitely won't take the vaccine to probably will take the vaccine. These minority populations are more likely to report the pandemic has had a major negative impact on their mental health and are more likely to know someone who has died from coronavirus compared to their counterparts. Studies have found many of those communities fear or have suspicion, and general distrust of the medical community. These lack of confidence barriers and negative perceptions about medical interventions, in general, and COVID-19 vaccinations, have been overcome in these communities through community outreach and education. In the final mile, those that refuse to be vaccinated will be asked to complete a survey to further understand their reluctance. We will design decision aids, incorporating information that serves to reduce anxiety about receiving vaccinations. The decision aids will provide accurate risk expectations. By addressing their concerns and the negative impacts experience as a result of the COVID-19 pandemic, we will help members of these vulnerable populations and family members to make choices that are consistent with their intrinsic values, and ultimate provide better health outcomes and reduce health disparities in these communities.

2.9 Summary of Literature Review on Vaccine Supply Chains for Pandemics

Author	Objective	Priority group	Methodology	Variables	Findings
Uscher-Pineset al. [13]	To review national pandemic influenza prioritization plans.	Healthcare workers, essential service providers, people at high risk, children, elderly, key decision-makers,influenza cases, hospitalized cases, and the unvaccinated	Descriptive statistics	Vaccine and antiviral priority groups, group rankings, goals of pharmaceutical interventions, the inclusion of scenarios and population size	Countries gave top prioritization to high-risk individuals, followed by health care workers,and service workers.
Buccieri and Gaetz [17]	To evaluate ethical pan demic planning policies	Homeless individuals in Toronto.	Mixed methods (descriptive statistics and interviews)	Gender, demographical factors, fear of infection, lack of concern access to community- based clinics, access to a regular doctor, pro- motional campaigns.	The findings showed that the immunization rate for the homeless was higher than the expected average rate
Govindan et al. [21]	To formulate a decision support system to manage the demand and to control the outbreak of an epidemic	Four categories based on the risk level of their immune system (very sensitive, sensitive, slightly sensitive, and normal).	Mamdani fuzzy inference system (FIS)	Fever, tiredness, and dry cough as the input variables. The output variable is the classification of the community members	The results for different scenarios confirmthat the proposed decision support system is sound and reliable.
Davila Payanet al. [18]	To explore the factors related to a vaccination cover-age rates of priority groups.	Children (6 months to 17 years) and high-risk adults(25-64 years).	Linear regression	State campaign information, demographics, preventive or health seeking behavior, preparedness funding, providers, state characteristics, and surveillance data.	The most significant factors of vaccine coverage rates are relatedto the distributional and systemic decisions.
Marcelloet al.	To estimate the number of vaccine doses administered.	None	Descriptive statistics	Facility type, number of doses administered, number of doses in stock, number of doses reported, and questions about the quality of communications.	The reporting about the pandemic vaccinewas visible across all vaccine providers.
Lee et al. [15]	To determine optimal vaccination allocation policies during the Spring	6 age groups (1 = 0–5 yrs, 2 = 6–12 yrs, 3 = 13–19 yrs, 4= 20–39 yrs, 5= 40–59 yrs,6= >60 yrs).	Non-linear dynamic mathematical model	Age distribution of the population, age- specific vaccine efficacy, hospitalization rates,	The population groupaged 20-39 must be given priority, followedby

	2009 H1N1 pandemic in Mexico.			mortality rates, and contact rates.	school children (6-12 years).
Arazet al. [16]	To identify the distribution policies that would be effective to reduce the pandemic's impact.	Preschool age children (0–4years), school age children (5–19 years), adults (20–64years), and older adults(65+ years).	Mathematical model	Transmission probability per contact, age- specific contact rate, force of infection, infectious period, incubation period, case fatality rate, vaccination rate, vaccine efficacy, vaccine pre-protection period, and numbers of people in each county and age-group.	***Pro rata*** distribution and prioritization of communities expectedto experience the latestoutbreak are the two most effective policies.
Fitzgerald et al. [40]	To analyze the importance of cooperation between public health agenciesand pandemic vaccine providers.	None	Descriptive Statistics	Data related to the public health program plans for the following: recruiting, enrolling, and registering pharmacists as pandemic influenza vaccine providers; vaccine allocation and distribution of pandemic vaccine to com- munity pharmacies; weekly allocation of pandemic influenza vaccine by provider type; and immunization policies, formalized agreements, and memoranda of understanding be- tween public health departments and community pharmacies.	Formalized agreements between public health departments and pharmacies should be established.
Medlock and Galvani [14]	To evaluate current vaccine allocation policies and to determine the optimal strategy.	17 age groups (ages 0, 1 to 4; 5 to 9; 10 to 14; ...; 70 to 74; and 75 and older).	Age-structured simulation model	Number of fatalities, contact rates, duration of the infectious period, years of life lost,weighing deaths against the expected remaining years of life for different ages, contingent valuation, costs associated with vaccination, costs associated with illness and death values.	Optimal vaccination is achieved by prioritization of schoolchildren and adults aged 30 to 39 years.
Biggerstaff et al. [19]	To analyze different vaccination scenario	People presenting to receive their second dose were prioritized over those receiving their first dose	A spreadsheet Simulation model	The number of people getting sick by time, the time difference between the launch of the vaccination program and emergence of the pandemic, the number of doses administered per week, and the allocation by age group, the clinical attack rate, hospitalization rate,	Strategies related to improvements in timeliness of vaccine production are crucial for future pandemic vaccination programs.

				vaccine effectiveness and case fatality ratios.	
Chen et al. [22]	To determine the optimal allocation policies for theCOVID-19 vaccine	Seven compartments (susceptible,exposed, pre-symptomatic infectious, unascertained infectious, ascertained infectious,isolated, and removed)and five age-groups (0-17, 18-44, 45-64, 65-74, and 75+).	Age-structured simulation model	The number of individuals in each of the seven compartments, the population size, the transmission rate, the contact rate, the dis- count factor of the transmission rate, the average times (from exposed to infectious, from pre-symptomatic infectious to symptomatic infectious, from symptomatic infectious to re- covered, from ascertained infectious to isolation, from isolation to recovered), the fraction of ascertainment for each age group, the levelof permitted economic activities, the amountof vaccine allocated to each age-group.	The results show that among the static policies, the optimal approach is to vaccinate the oldest group first and then the younger group. In the case of dynamic policies, the results reveal that the best policies are myopic and two-day myopic.
Huang et al. [20]	To explore the optimal al- location of several vaccine types to certain priority groups.	Pregnant women, infants (0-3 years old); people be- tween age 4-24; and adults at high risk and infant care-givers.	Optimization model	The five priority groups and regions were takenas input.	A small cache of discretionar y doses is enoughto achieve the vaccine's optimal distribution.

Chapter 3: Artificial Intelligence and Automated Data Capture Needed to Automate Healthcare Supply Chain

3 Chapter 3: Artificial Intelligence and Automated Data Capture Needed to Automate Healthcare Supply Chain

3.1 Background

3.1.1 The use of Artificial Intelligence and Deep Learning to Predict Diseases

Recent developments in autonomous AI and machines learning have offered great potential in healthcare sector. It offers not only to improve the healthcare productivity, but also lowering the healthcare related costs, and improving the accessibility of quality healthcare options globally. Several researchers are focusing on developing algorithms to detect diseases using eyes, while others are focusing on facial features to detect different type of diseases.

Even though most of the research studies related to AI and machine learning in healthcare sector are in trail phase, we already have seen some great systems developed already and available in the market. One of the biggest landmarks in this regard is FDA's approval of artificial intelligence-based device to detect certain diabetes related eye problems on April 11, 2018 [1]. The approval was given by FDA to market a device called IDx-DR, which uses artificial intelligence to detect mild level of eye disease diabetic retinopathy in adults who have diabetes [1]. This device uses AI algorithm to analyze digital retinal images taken with retinal camera and uploaded on cloud server by the doctor. Based on the uploaded image, the software will give results that whether the sickness is detected or not and what further protocols need to be followed. FDA authorities also said that they will continue to facilitate such devices in future which improve access of required healthcare to patients.

Another very recent study led by researchers predicts the risk of heart attack in patients through retinal scans using artificial intelligence algorithm [2]. The algorithm predicts the risk of myocardial infarction using just the retinal images and demographic data and results can identify patients at high risk of future myocardial infarction and a risk of heart attack within the next 12 months with an accuracy between 70% and 80%, using the retinal imaging [2]. The deep learning approach used in this research is multichannel variational autoencoder (mcVAE) and a deep regression network ResNet50.

Another study [3] used artificial intelligence-based diagnostic to detect the early signs of glaucoma 18 month earlier than the traditional testing methods. They used the CNN-aided method (Convolutional Neural Networks) to predict glaucoma progression using DARC Images (Detection of Apoptosing Retinal Cells). The company Tesseract raised $80 Millions to develop retinal scanning systems that aimed to diagnose a wide range of diseases. Tesseract's iC platform combines chemical sensors, imaging technology and artificial intelligence analyses to inspect the back of the eye to provide automated clinical diagnostics [4].

3.1.2 A Future of COVID-19 Treatment without Vaccine and painful Needles

Ever since the beginning of COVID-19 Pandemic, researchers from all across the world have been investigating different options for the treatment of SARS-COV-2. This is really critical even after two years from the start of pandemic due to different variants resulting in new waves of this virus spreading globally. In this regard, December 22 and 23rd, 2021 are landmark days, when FDA granted authorization to Pfizer's Paxlovid and Merck's Mlnupiravir (COVID-19 Oral Antiviral products) for emergency use (EUA) [1]. Patrizia Cavazzoni, M.D., director of the FDA's Center for Drug Evaluation and Research described this a major step forward in the fight against this global pandemic," [1]. Ever since, Merck sold $952 million of its Covid-19 treatment pill molnupiravir in the fourth quarter, and said it's on track for an additional $5 billion to $6 billion in sales in 2022 with most sales so far concentrated in the U.S., the U.K. and Japan [2].

The clinical trials of molnupiravir started in October 19, 2020 and anticipated study completion date is May 5, 2022 [3]. The initial results show some promise with reduced the risk of hospitalization or death in Covid patients by 30% but slashed the risk of dying by 90% [2].

Another recent invention from MIT engineers [4] provided another option of delivering mRNA vaccine to patients without the use of vaccine or needles. This invention is targeted for those people who are reluctant to take COVID-19 vaccine due to discomfort of being jabbed or inserting needles inside them. They have invented a tiny device, "the size of a large pill, encased in gelatine and shaped like the shell of a tortoise. It carries a needle that is engineered to only lance out when the device's flat section sits flush with the lining of the stomach [4]." So far the study is in initial phase with some trails conducted on animals, but the results are so far inconclusive.

Despite these significant developments in recent months, neither Paxlovid nor molnupiravir is authorized for pre-exposure or post-exposure prevention of COVID-19, and neither can substitute the need for vaccination. Despite the availability of these medications for some people, it's critical for everyone who can get vaccinated to get vaccinated against COVID-19 [5]. Even with all of this, it is extremely essential that scientists and researcher should come up with alternate treatment of COVID-19, which are less painful and effective against all variants, and the developments like oral antiviral pills or needleless administration of vaccines provide a lot of optimism.

3.2 Sickness Detection Model

3.2.1 Approach

In this section, we will discuss the approach that we used to train the model for predicting sick vs healthy based on facial features and thermal imaging. We will discuss the dataset that we have used to train and test the model, how the data was processed, which deep learning model did we use and results and discussion on outcomes vs expected results..

3.2.1.1 <u>Dataset</u>

In the study, we have considered the dataset that had images of people with different facial orientations, sizes, backgrounds, ethnicity, and different races to make sure our model is not biased. We have considered an even split of both features of the model – sick (300 images) and healthy(320 images) people. For training and testing our model, we have considered a split of 80% training data and 20% testing data.

3.2.1.2 <u>Preprocessing Data</u>

The first step of the sickness detection model includes data preprocessing like normalization, face detection, grayscale conversion, and standardization of our data to ensure proper detection of the different classes of data. There are multiple face detection algorithms developed over the years that are used to detect faces in a single image. One of the most successful algorithms to detect visual images or live video is Viola-Jones Face Detection Technique, popularly known as Haar Cascades[x]. This is a proven object detection algorithm that gets results rapidly and with high detection rates. The process involves converting the image to grayscale and resizing the image to focus on the face area. The images are then randomized and converted to a NumPy array.

3.2.1.3 <u>Building the CNN architecture and training the model</u>

A convolutional neural network (CNN) is a type of artificial neural network used in image processing to process pixel data. There are 3 layers in a CNN model - an input layer, an output layer, and a hidden layer that has multiple convolutional layers, pooling layers, fully connected layers, and normalization layers.

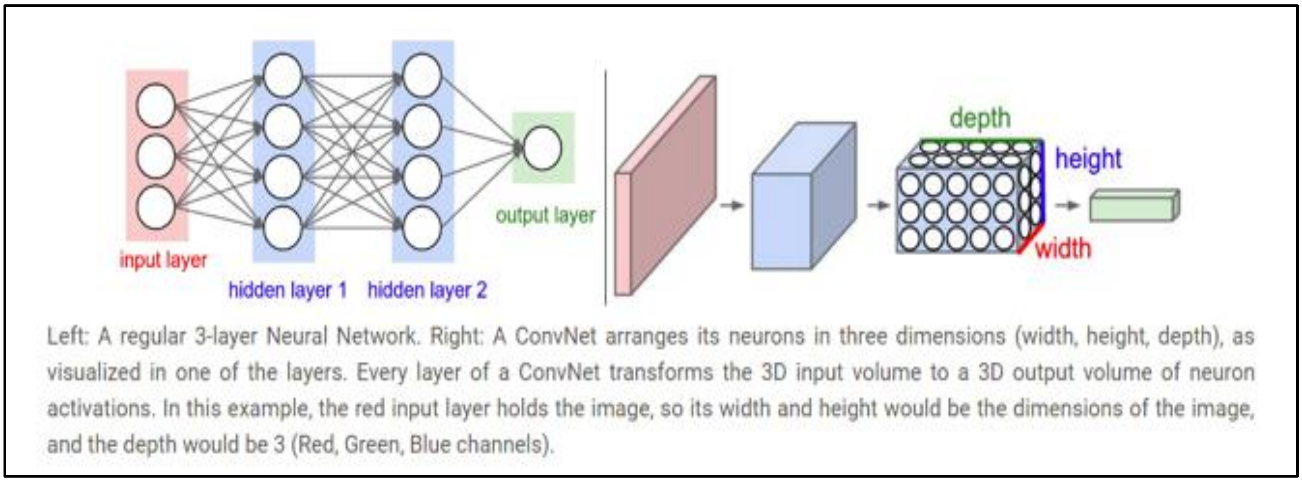


Figure 3-1: Demonstration of three layers in a CNN model

The model takes inputs as an image which is a matrix of pixels and assigns weights and biases to different aspects of an image to differentiate from one other. The objective of the convolutional layers is to extract high-level features from the input. The initial layers of the models detect the curves, edges, gradients, and orientations. As the model progresses further into deeper layers of the network the various other high-level features of the images are identified.

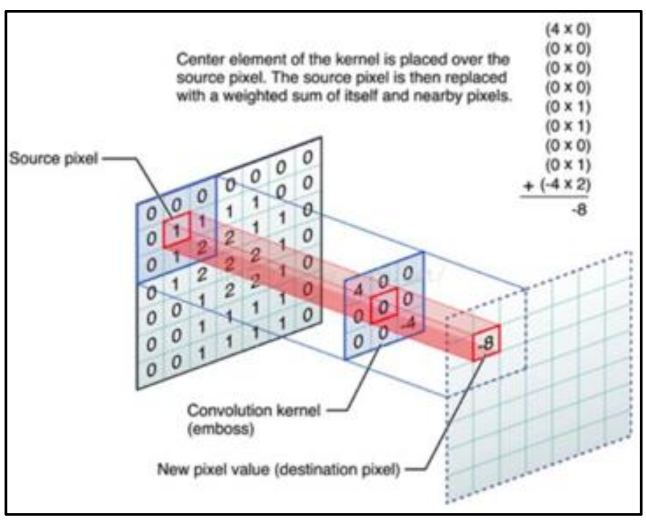


Figure 3-2: Progression of CNN model into further deep layers

The performance of the model is also influenced by the activation function used. To handle the complex neural nets non-linear activation functions like sigmoid, hyperbolic tangent (tanh), and rectifiedlinear unit (ReLU) are used. We have used the ReLu activation function for our research

$$\text{rectified linear function,}\quad f(x) = max(0, x)$$

We used two ConvNet layers each layer followed by ReLu and max-pooling layers followed by flattening and dense layers. The output layer has 2 nodes which the model predicts as sick vs healthy patients

3.2.2 Data Collection

In the study, We have collected the data of about 620 images of both sick (300 images) and healthy(320 images). All images were converted to grayscale, face detected, and standardized. A CNN model was trained with multiple layers to detect the patient's health status. We have trained the model for 50 epochs to attain the desired accuracy. We also ran the model by adding more layers to the architecture to predict the depth of the image and identify more features.

Table 3-1: Details of dataset used to train the model

Status of patient	**Gender**		**Age groups**		
	Male	Female	Kids	Adults	Elders
Sick	30%	70%	25%	55%	20%
Healthy	25%	75%	20%	45%	35%

Figure 3-3 shows some images of sick people used for training our model
(https://github.com/J1C4F8/deep_learning_acute_illness)

Figure 3-3 shows the images of sick people that were used to train the CNN model for predicting sickness. As we can observe, the facial features of sick people are clearly different than the images taken when they were healthy. The facial features like lips color, eye dilation, eye color, paleness, redness of nose and lowered cheekbones were some of the features that were learnt by the model.

Figure 3-4 shows some images of healthy people used for training our model (https://github.com/J1C4F8/deep_learning_acute_illness)

3.2.3 Results and Discussion

In order to predict sick vs healthy using deep learning algorithm, we need a huge dataset for model to accurately make predictions. Based on the dataset that we used to train our model ran the test implementation of our model, we were able to achieve high training accuracy and the model was able to predict during the live video stream. Below are the images that show the distinction between sick and healthy patients.

Output-1

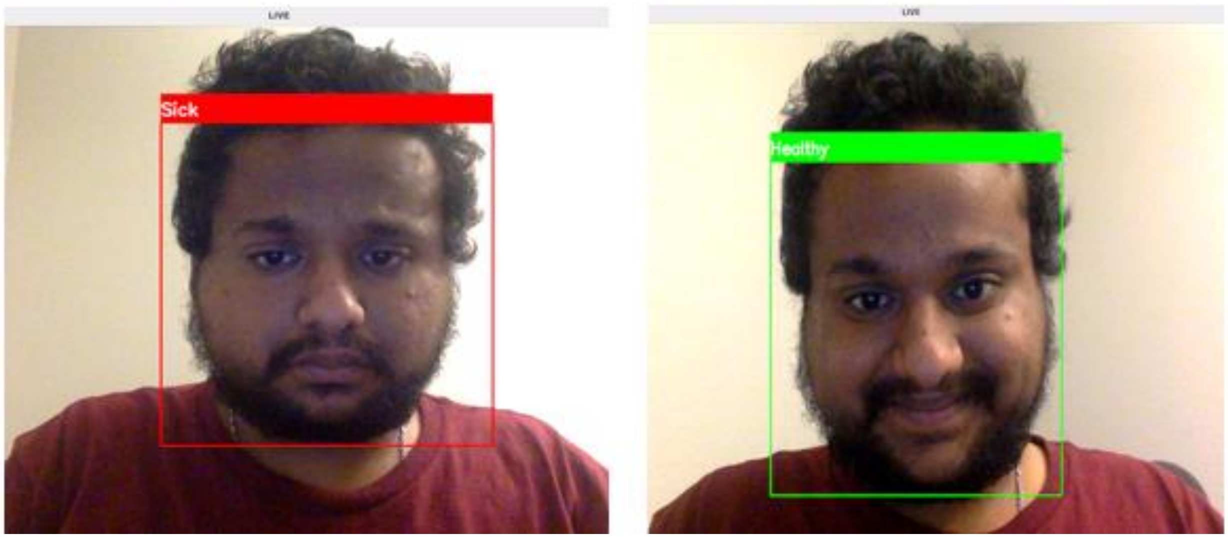


Figure 3-5: Sample Output 1 of Sickness detection model predicting sick and healthy

Output-2

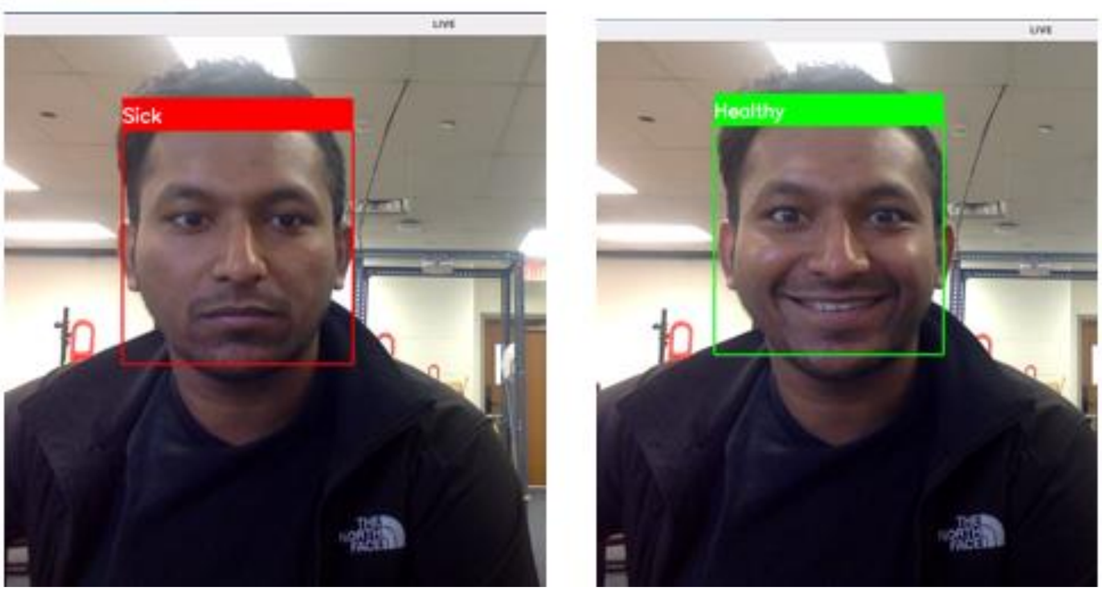


Figure 3-6: Sample Output 2 of Sickness detection model predicting sick and healthy

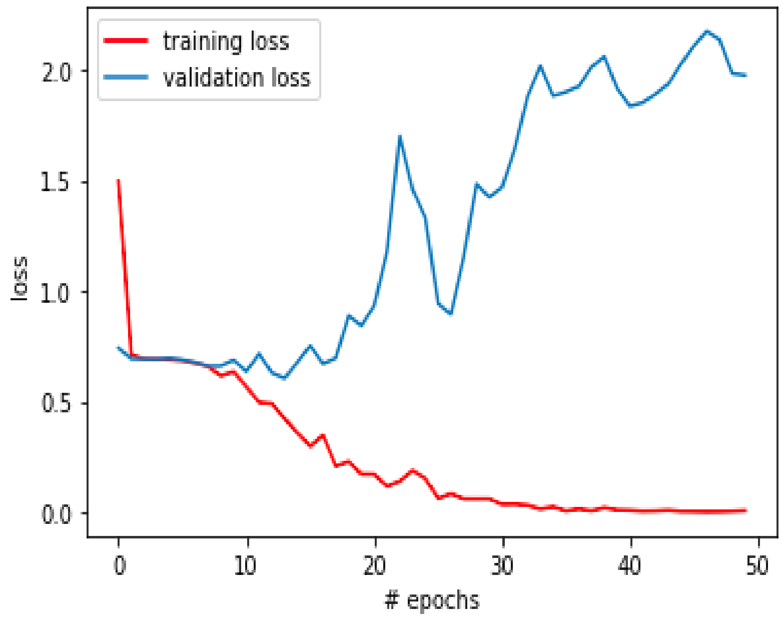


Figure 3-7: Graph showing Training loss and validation loss

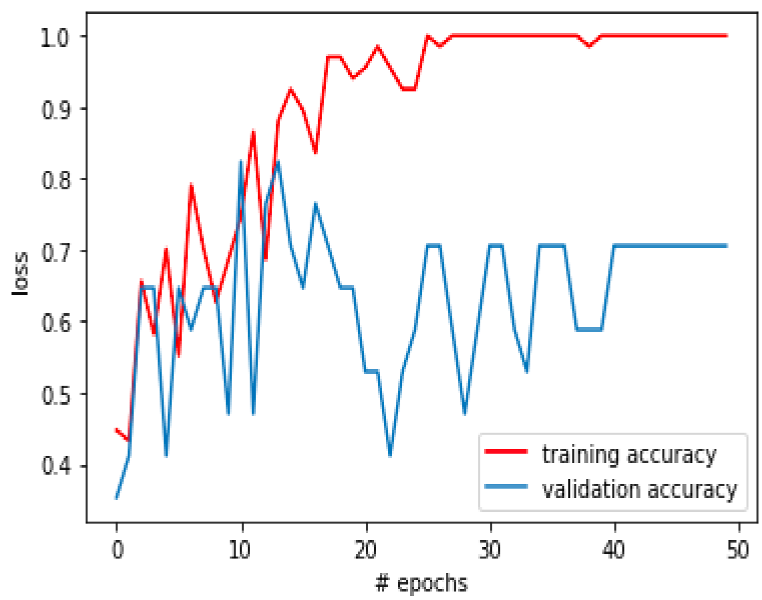


Figure 3-8: Graph showing Training accuracy and validation accuracy

In the graphs, the training loss is decreasing gradually over the epochs which is an indication that the model is fitting well with the training data but since the dataset is small the validation loss is higher. Based on the output, we were successfully able to get the training accuracy of above 70%. The validation accuracy is still between 60%-70% which can be further improved as we use more dataset of images to train the model.

As stated in chapter 1, the hypothesis for sickness detection is given below.

H_0: The AI enabled model will accurately detect sickness through thermal imaging and facial recognition with accuracy of above 70%

H_1: The AI enabled model will not accurately detect sickness through thermal imaging and facial recognition with accuracy of less than 70%

Based on the accuracy of output we have achieved so far, we were successfully able to get the training accuracy of above 70%. The validation accuracy is still between 60%-70% which can be further improved as we use more dataset of images to train the model. We are quite hopeful that validation accuracy of the model will eventually improve to above 80% as we use more dataset to train the model in future.

3.2.4 Conclusion:

The study presents a system that can detect if a person is sick or healthy using facial characteristics. Experiments show that the system can predict between sick and healthy individuals with high training accuracy of above 80%. Due to limitations of data in practical deployment, we were not able to achieve higher validation accuracy for our model. This is due to the requirement of a large dataset of images to train the deep learning algorithm. However, we hope this system would be the first step towards detecting sickness we plan to implement further on this and detect deep features like the color of skin, redness of the nose, and eye shapes to classify and detect diseases.

3.3 Pill Consumption Confirmation Model

Drug monitoring accurately and collecting the data can help us to better understand the results of therapeutic trials. Our proposed system will help the user to take their medicines on time without much cost. Our application will help users to take their medicines at the required time. The application will check whether the patient has taken the pill or not. Computer-aided diagnosis enables us to carry out the check-up quickly and easily. Therefore, if diagnosis can be proved effective with an acceptable error rate, it will be with enormous potential. With the help of artificial intelligence, we could explore the relationship between pill consumption and disease with a quantitative approach. The present report describes medication adherence results from an exploratory pilot sub study, using the AI platform using Mobile Application that was evaluated for treatment of cognitive impairment in patients with Alzheimer. The objectives of this exploratory pilot sub study were to evaluate the AI platform as a real-time monitoring method for study drug adherence, and to examine the feasibility of using the platform Alzheimer study.

3.3.1 Approach:

In our application to monitor the Pill consumption, we are using a single Shot detector takes only one shot to detect multiple objects present in an image using a multi-box. MobileNet is a lightweight Neural Network architecture designed for mobiles and embedded vision applications.

3.3.1.1 Data Collection:

For the purpose of training the model, videos were captured with iPhones of several participants consuming the pill and also pretending to consume the pill which should also be identified as Pill not consumed. Videos were captured with people of different backgrounds and colors to ensure minimal biasness in model prediction. People from the lab volunteered to record videos for training and testing of the model. The videos were also recorded in different environments such as consuming pill in rooms with enough light vs consuming pill in darker rooms. The videos were converted into images and the data was split into train and test where training images were 200 and test images were 60 (70-30 Spilt). For Data Annotation, labelImg tool was used to annotate the images. We have defined four classes namely

- Tablet_Presence,
- Tablet_Absence,
- Pill_Consumed,
- Pill_Not_Consumed..

Table 3-2: Split of Training Data vs Testing Data

Training Data (Images)	Test Data (Images)
200 Images (70%)	60 Images (30%)

3.3.1.2 Preparing and Training model:

Now that we have images and their corresponding .XML files and the TensorFlow model accepts the input in terms of .tfrecords, so to get that first, we needed to convert .xml files to .csv and once the conversion was done, the train.csv and test.csv files are proofread for any wrong naming of classes apart from defined classes. Post that we ran the generate_tfrecord.py file to generate train.record and test.record files. For training the model we have used Tensorflow 2.4. which is trained for 14k steps using CUDA GPU in Windows 10 and model architecture used was SSD MobileNet V2.

Testing: The model was tested on 15 unseen data setting the min_threshold_score =0.95 which means the model should detect only the classes which have confident scores equal to or more than 95% accurate. We also built an web application using Node JS which captures the video of patients and predicts whether tablet is present, absent, consumed or not consumed. We have also integrated IBM Cloud to store and access our data.(In detail will be explained in next draft)

3.3.2 Results:

Below are some of the Graphs which show the results of model training and testing and depicting the model training rate and loss rate.

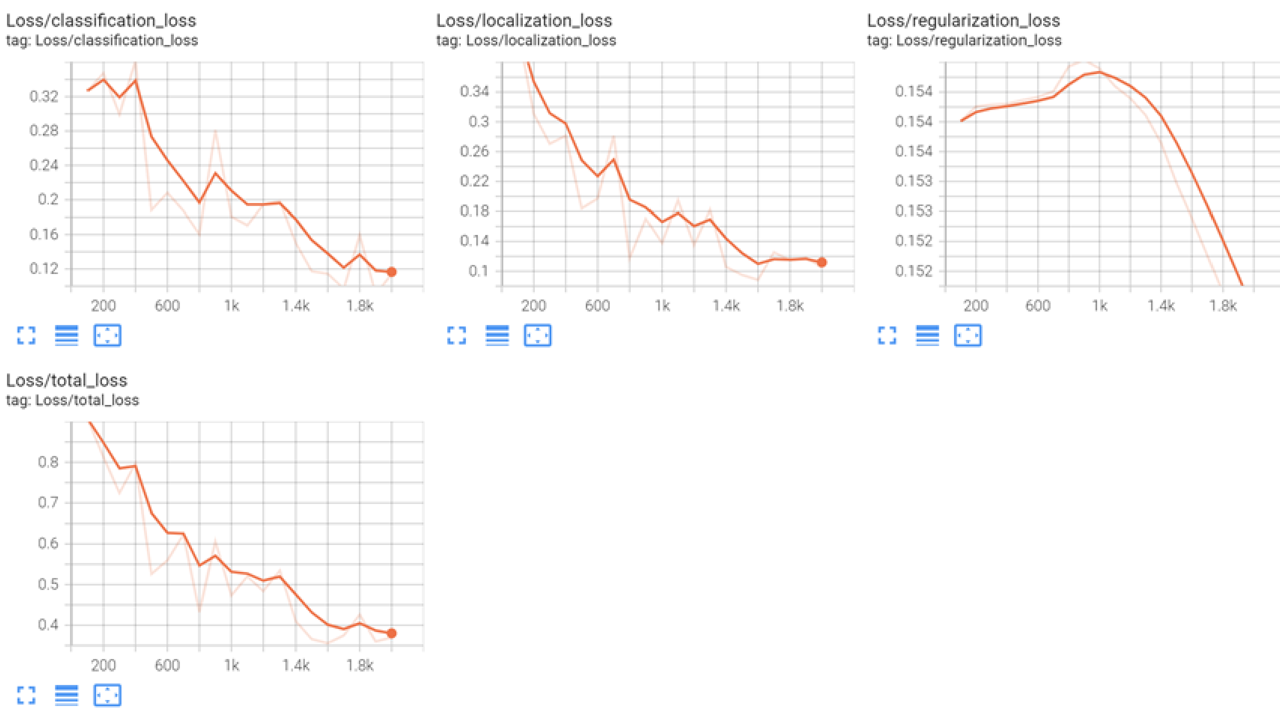


Figure 3-9: Graphs showing Loss Rate of Pill Consumption Confirmation Model

The loss value given is a sum of the classification loss and the localization loss. The optimization algorithms are trying to reduce these loss values until your loss sum reaches a point where you are happy with the results and consider your network 'trained'. We can generally think of loss as a score where 'lower score equals better model'. We can see in Fig 3-10, loss rate is decreasing which shows ours model is predicting accurately.

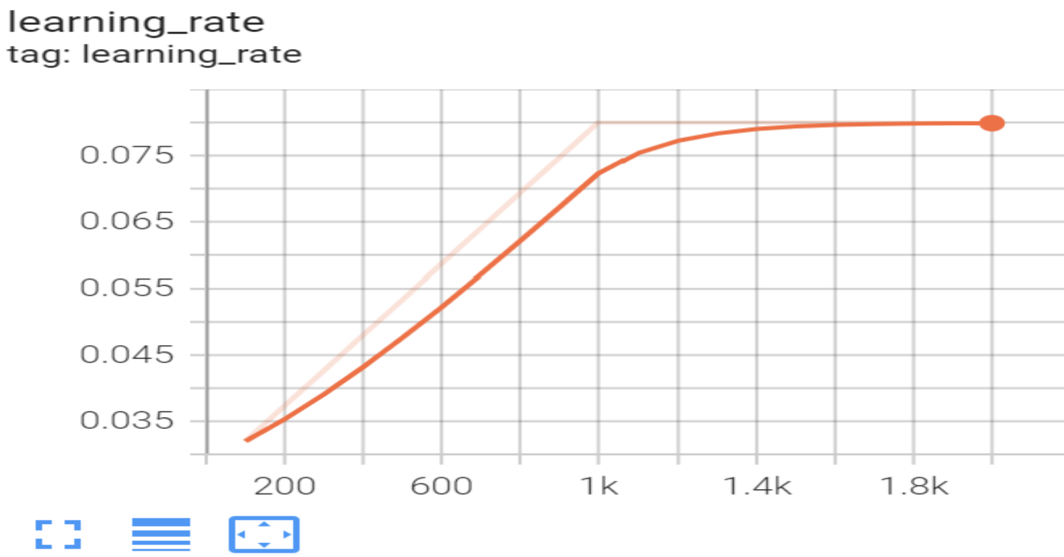


Figure 3-10: Graphs showing Learning Rate of Pill Consumption Confirmation Model

In this graph, the training rate is increasing over the epochs which is an indication that the model is fitting well with the training data. As seen in the graph, an accuracy of above 80% was achieved for predicting that whether or not the pill has been consumed by patient. Accuracy can further be improved by tuning the data. The increase in the number of data values will help the system to predict more accurately in future.

3.3.3 <u>Conclusion:</u>

As stated in chapter 1, we stated the hypothesis for pill consumption confirmation.

H_0: The "Pill Consumption Confirmation" Telemedicine model will accurately verify pill confirmation process with accuracy of above 70%.

H_1: The "Pill Consumption Confirmation" Telemedicine model will not accurately verify pill confirmation process with accuracy of less than 70%.

As we were able to achieve accuracy of above 80% for successfully verifying the pill consumption process, we reject H1: The "Pill Consumption Confirmation" Telemedicine model will not accurately verify pill confirmation process with accuracy of less than 70%. Hence we have met our objective.

3.3.4 Model Outputs:

As seen in figures 3-12 and 3-13, we can see that our model is accurately predicting the pill consumption activity with high accuracy > 80%.

Figure 3-11: Output 1 of Pill Consumption model identifying pill consumption activity

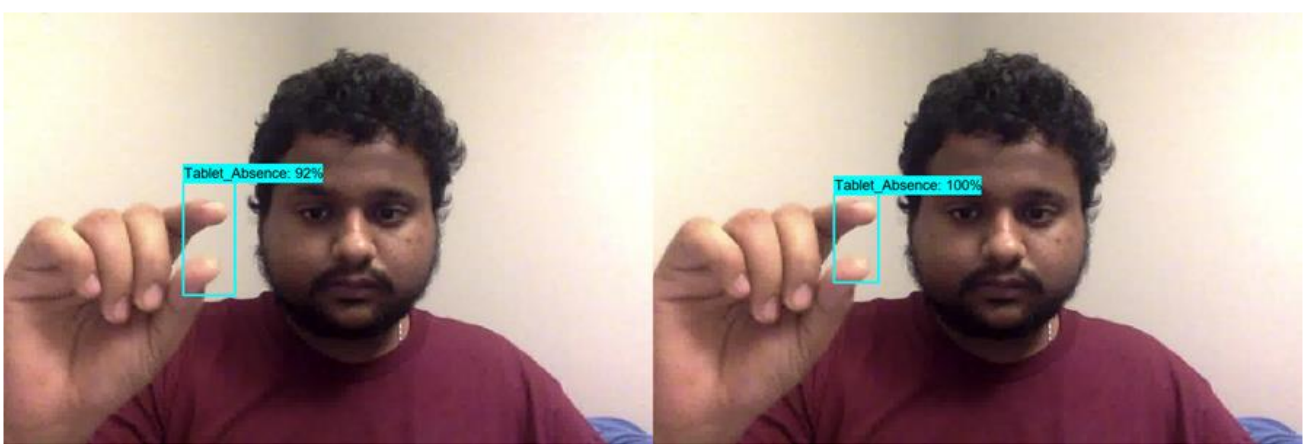


Figure 3-12: Output 2 of Pill Consumption model identifying no pill

Chapter 4: Optimized Healthcare Supply Chain Model for at-risk communities

4 Chapter 4: Optimized Healthcare Supply Chain Model for at-risk communities

4.1 Background

In addition to disruption in every field of life, COVID-19 has also brought to light the inequity of access to health care, treatments, and diagnostic testing. This inequity will also impact vaccine distribution and administration, particularly among low and middle-income families. As WHO director Dr. Tedros said, “The world is on the brink of a catastrophic moral failure, and it will be paid with lives and livelihoods in the world’s poorest countries.” This model is aimed to acknowledge the barriers to an equitable vaccine distribution system, inspire us to protect our most vulnerable populations, and emerge from this global pandemic stronger together.

Vaccines are a crucial drug during times such as these, the supply chain distribution of it is highly sensitive and access of vaccination centers are often skewed away from underserved communities. Optimizing COVID-19 vaccine distribution can help plan around the limited production and distribution of vaccines, particularly in early stages of the pandemic. One of the ways for equitable distribution of vaccines is prioritizing the underserved communities. During the pandemic, the last mile transportation concept was crucial for saving lives for underserved populations. The supply chain model then maximizes social welfare benefits by sending drugs to underserved communities regardless of their ability to pay.

In previous research referred before, most of them focused on studying vaccine distribution, designing cold chain networks, using machine learning for demand forecasting. Despite the substantial published research on vaccine hesitancy among the underserved communities, very few related studies are concerned with problems related to the vaccine distribution and the supply chain network optimized to prioritize the underserved communities.

The process of designing and setting up a vaccine distribution network for the underserved communities is a difficult task. In the development of an optimized supply chain network, we must introduce the constraints of vaccine production at the manufacturer side and vaccine storage limits at the hubs. Prioritizing zip codes with a large proportion of underserved communities and higher CHI index is one way to develop an efficient vaccine distribution supply chain network. The final output of the optimization will give a set of prioritized zip codes with penalty costs added to respective zip codes.

4.1.1 Vaccine Supply Chains

Vaccine supply chains consist of their own performance metrics such as scale, exposure, time space levels and constraints such as manufacturing limits. Most of the studies done so far focuses on the procurement, shipping, and optimizing distribution of the vaccines to the customers. The decision at distributor level to use a cold chain or non-cold chain to transport the vaccines is critical for vaccine distribution [1]. Experimental and simulation studies of ultra-low temperature refrigeration system is important as Pfizer vaccine requires ultra-low temperature storage (between −80 °C and −60 °C), while the Moderna vaccine requires −30 °C storage, Pfizer has designed a reusable package for transportation and storage that can keep the vaccine at the target temperature for 10 days [2].

Supply chain designing for vaccine distribution is anything but an easy task as it deals with complex vaccine chemistry with a delicate delivery system – The challenge is to keep vaccines at a suitable temperature so as to not reduce its efficacy [1][10]. There are two major ways for vaccine distribution but considering that we are primarily focused on developing COVID-19 vaccine supply chain system we base our research on the cold chain system for delivering the crucial drug. Cold chain supply system primarily delivers vaccines in either in generic insulated pharmaceutical box[2] or in cold chain mixes like domestic or absorption type fridges[11]

4.1.2 Machine Learning Algorithms used in Supply Chain Systems

This section discusses some of the most common used algorithms used for optimizing supply chain systems.

The **K-Nearest Neighbor algorithm** is based on the Supervised Learning technique and is one of the most basic Machine Learning algorithms. The K-NN method assumes that the new case/data and existing cases are similar and places the new case in the category that is most similar to the existing categories. The K-NN method stores all available data and classifies a new data point based on its similarity to the existing data. This means that new data can be quickly sorted into a well-defined category using the K-NN method. The K-NN approach can be used for both regression and classification, but it is more commonly utilized for classification tasks. The K-NN algorithm is a non-parametric algorithm, which means it makes no assumptions about the underlying data. It's also known as a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset. K-NN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

K-Means Clustering is a type of Unsupervised Learning method that divides an unlabeled dataset into groups. K specifies the number of predefined clusters that must be produced during the process; for example, if K=2, two clusters will be created, and if K=3, three clusters will be created, and so on. It allows us to cluster data into different groups and provides a simple technique to determine the categories of groups in an unlabeled dataset without any training. It's a centroid-based approach, which means that each cluster has its own centroid. The main goal of this technique is to reduce the sum of distances between data points and the clusters that they belong to. The unlabeled dataset is sent into the algorithm, divides the dataset into k-number of clusters and repeats the process until it does not find the best clusters. The value of k should be predetermined in this algorithm.

Dijkstra's Shortest Path Algorithm - This algorithm finds the shortest path from a single source node to all other nodes. Nodes are represented by colored circles and edges are represented by lines connecting those circles. The algorithm keeps track of the shortest currently known distance from each node to the source node and updates these values as shorter paths are found. If the algorithm finds the shortest path between the source node and another node, that node is marked as "visited" and added to the path. This process continues until all the nodes in the diagram have been added to the path. In this way, there is a path that connects the source node to all other nodes and follows the shortest path to reach each node. Dijkstra's algorithm works only on graphs with positive weights.

The **Decision Tree algorithm** is the most powerful and popular tool for classification and prediction. The decision tree is a flow chart-like tree structure, where each internal node specifies a test for the attribute, each branch represents the result of the test, and each leaf node (terminal node) contains a class label.

A **recurrent neural network (RNN)** is a neural network used to process sequential data, including those with text, sentences, audio, video, or sequences. RNNs work by evaluating information before input and predicting information after or after. RNNs help predict contextual information such as incomplete sentence endings and a series of voices.

4.1.3 <u>Machine Learning Models used in Vaccine Supply</u>

For forecasting time series data, the Auto-Regressive Integrated Moving Average (ARIMA) and Multilayer Perceptron Neural Network (MLPNN) models were used, and a study found that the best forecast model was chosen based on the lowest Root Mean Square Error (RMSE) value and the Mean Absolute Error (MAE) (MAE). The MLPNN model outperformed the ARIMA model in projecting monthly vaccine demand, according to the analysis[3]

LSTM networks are an extension of recurrent neural networks (RNNs) in a deterministic Long Short Term Memory (LSTM) model, primarily created to address instances where RNNs fail. When it comes to RNNs, they are networks that work on current inputs while considering prior outputs (feedback) and storing them in memory for a brief period of time (short-term memory). The number of confirmed cases and the value of effective reproduction number in the next time step are the network outputs.

Mixed Density Network (MDN) is an interesting model format built into the general framework of neural networks, probabilities for tackling supervised learning problems where a single standard probability distribution cannot easily approximate target variables. The network output in the stochastic MDN (Mixture Density Network) model is mixture distribution parameters rather than a direct prediction value. The suggested MDN model consists of a blend of LSTM layers and distributions. LSTM layers provide parameters for one or more distributions in this model, which are subsequently coupled with weighting.

LSTM RNN is useful because more confirmed cases can lead to greater potential infection in future populations, therefore maintaining all relevant historical information is critical. The deterministic LSTM model exhibited better performance than the stochastic LSTM/MDN and linear regression models. However, the stochastic model was more successful in predicting the trends in the actual dataset[4].

4.1.4 The need for vaccine supply chain optimization:

The biggest challenge during the pandemic times other than development of therapeutics for fighting the virus was optimizing the supply chain for vaccine distribution. Although there are several studies done on optimizing the supply chain system for delivering COVID-19 vaccines safely, very few studies have been done in optimizing the network to prioritize the most affected in society.

There are reports that show that the underserved in our community have been hesitant towards adopting new vaccines because of historic atrocities that these communities have faced in the years past. Also, the present disparity in health care setup, the access to which at present is skewed away from the underserved communities this future aggravates this socio-economic disparity that these communities are already facing. After accounting for the factors such as Socio-economic status, Household composition, Minority status and Housing type, We came up with a metric to define the vulnerability of these underserved communities, This metric is called CHI (Community Health Index), It's discussed in detail in the coming sections.

4.2 Approach

The global activities during pandemic influenced the strategies real-time including testing protocols, ventilators distribution, and vaccine manufacturing, which impacted the strategies in real-time. Our research objective is to understand how the COVID-19 therapeutics (Immunizations, drugs etc.) can be delivered to underserved communities including the last mile transportation, to prevent and minimize the impacts of COVID-19. For this NSF funded study, we are focusing on the city of Houston, which is the fourth largest city in US. We worked with the City of Houston Health Department (HHD) to capture the data needed to model a community that has these challenges. The Houston Department of Health and Human Services HHD has the responsibility for community health, particularly for the underserved population that might not have commercial insurance plans (Medicaid and Medicare). The HHD also has an elderly care division that distributes care between the services facilities, the hospitals and home care. Our research focuses initially on the most vulnerable population for the COVID-19 population, namely the elderly in underserved populations who receive personal home services from HHD. For this study, we will focus on 96 zip codes in city of Houston.

4.3 Data Collection

For data collection, we collaborated with City of Houston Health Department. At the time of data collection, we were in phase I of COVID-19 vaccine distribution where demand was far higher than the supply of vaccines; we considered the elderly population and healthcare workers as the actual demand, which is 20% of the total population as per the collected data. The number of vaccination administration points, including hospitals, pharmacies and other locations at the time of data collection was 256 in Houston with 4 major central hubs in Houston providing vaccine shipments to these locations.

Table 4-1: Assumption and data collection details

Assumptions and Data Collected	Measure
Total Zip Codes considered in Harris County (77002-77099)	96
Total Hospital/pharmacies/nursing homes in Harris county considered in our model	256
Total vaccine hubs in Houston for distribution	4
Population of all zip-codes in Harris County	3,270,360
20% population of all zip-codes for elderly population	654,072
Cost of transportation/mile	$1
Penalty cost for any shortage	$35-$70
Total complete communities in Harris County	10

We worked with HHD to collect the COVID-19 related data in these zip codes including the total number of reported cases in each zone, number of active cases and total number of deaths.

Initially, we assume our current demand (dj) is the total number of cases reported in each zone for modelling supply chain. We collected the data during the first phase of COVID-19 vaccine distribution where demand was much higher than the availability of vaccines supply, so we will be focusing on elderly population above the age of 60 and healthcare workers, who were supposed to get the vaccine at the earliest.

As mentioned previously, we want to highlight and prioritize the communities, which are at high risk or are more vulnerable to COVID-19 outbreak. In this study, we defined a new term called "Community Health Index (CHI)". The CHI is calculated using a proprietary modified health index that takes into account social-economic indicators and has the ability to use artificial intelligence for behavior patterning. The data for modified health index and other indicators for different regions has been provided by HHD, which is used to calculate the community health index. This CHI helps us in identifying those communities, which house the most vulnerable populations. We can use this information in our mixed integer programming (MIP) optimized supply chain model to prioritize these communities using the concept of higher service level. The CHI is calculated using below equation (Jones et. al 2020).

Community Health Index = (Modified Health Index + Social-Economic Index + Behavior Index) / 3

Health Index: (modified RTN) with heavier weighting of the HHD 8 health factors from the questionnaire. Our health index is based on Houston's Vulnerability Index, a mostly health focused indicator. However, they added some additional data so that it could be used to identify who needs help in an emergency like a hurricane or extreme flooding.

Socio-Economic Index: Combination of different indicators such as education, average income etc. in different zones. Our Socioeconomic Index is based on the CDC's Social Vulnerability Index, which takes into account socioeconomic status, household compositions and disability, minority status and language, and housing type and transportation.

Behavioral Index: We are also using the COVID-19 active case information to inform our CHI. In the future we plan to use AI to determine who is at risk and who will need treatment soon.

By taking all three of these indices, we produce one simple CHI score. That CHI score can be used into the supply chain model and prioritize treatment shipments. The higher the CHI rate, more vulnerable that zone is to COVID-19.

4.4 Multi-objective optimization and supplier selection in supply chains

The existing literature primarily focuses on optimization of one objective function viz cost or profit and other important factors such as customer service and vendor management are neglected. Since we seek to optimize off of community and to prioritize geographic regions in supply chain model on the basis of service levels, we will use multi-objective optimization. There are multiple techniques for multi-objective optimization such as Σ-constrained method, sequential optimization, weighted method, and distance-based model. Franca and Jones 2010 introduced a multi- objective stochastic supply chain model that incorporates Six Sigma approach to assess the financial risk. The model consists of design of four-echelon supply chain that includes identifying objectives, establishing model constraints, evaluating the economic risk & formulation of model by multi-objective Σ constrained method. In this paper, we utilize the Σ-constrained method to optimize profits and quality objective function. In the below figure, the four-echelon supply chain configuration is shown. The most important part of this supply chain is last mile transportation from hospitals or therapeutics distribution points to underserved communities. This last mile transportation is critical in saving lives during the pandemic for these underserved populations.

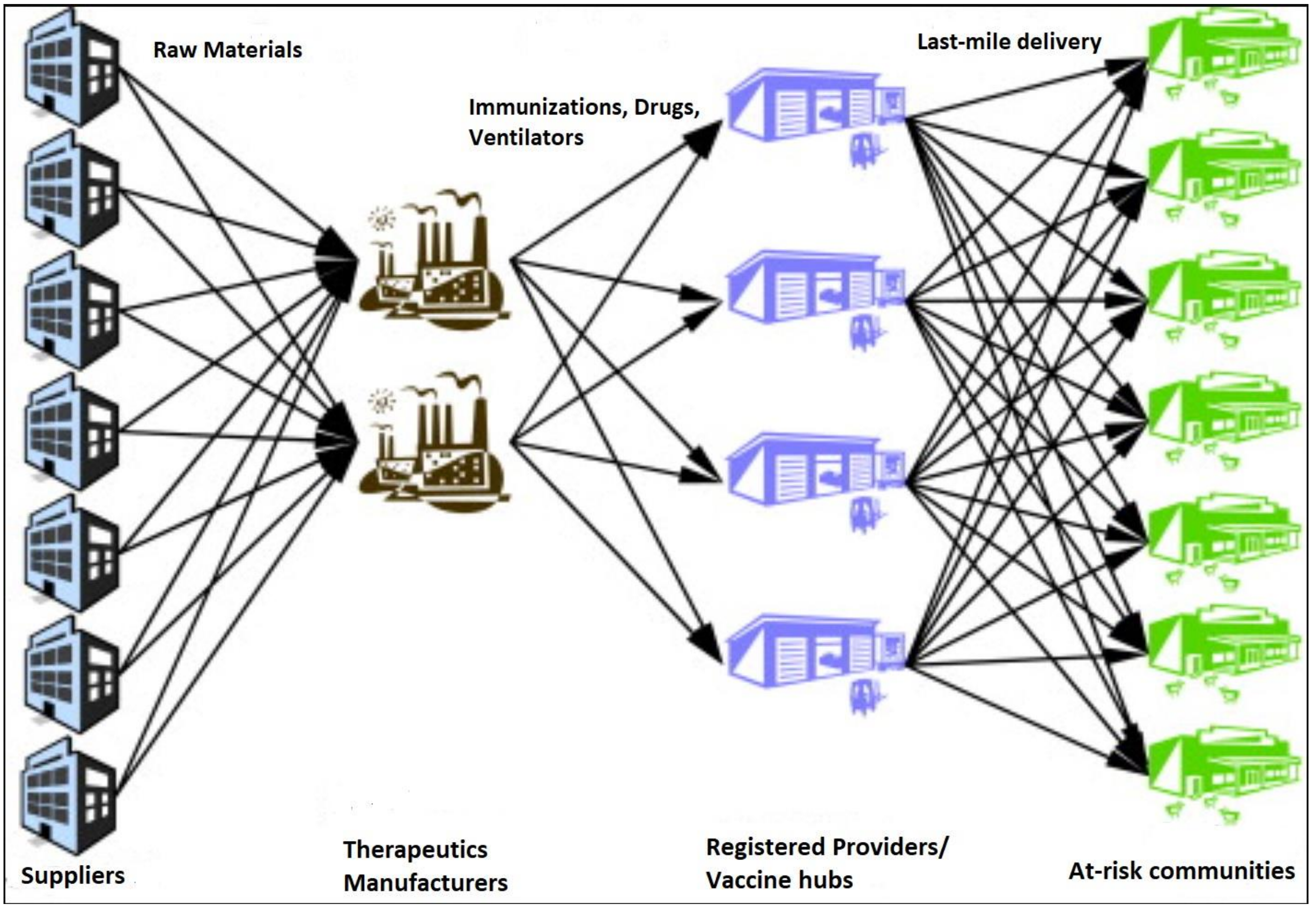


Figure 4-1: Jones and Azeem's Echelon Supply Chain Configuration (Modified from Franca and Jones, 2010)

4.5 Mathematical Model

This model is based on the supply network design problem. Given a set of producers, depots, and customers (zip codes), the goal is to determine how to satisfy customer demand while minimizing transport costs and service. This problem can be regarded as one of finding minimum cost flow through a network. Our primary objective is to ensure that the immunizations and the drugs are delivered to required population when required, so we use higher service levels for regions that are highly vulnerable to COVID-19.

4.5.1 Sets and Indices

$$f \in Producers = \{Producer\}$$

$d \in Depots = \{D1, D2, D3, D4, D5\}$

$c \in Customers = \{C1, C2, C3, C4, C5, C6, C7, C8, C9, C10\}$

$Sets = Producers \cup Depots \cup Customers$

4.5.2 <u>Parameters</u>

$cost_{s,t} \in \mathbb{R}^{+} : Cost\ of\ shipping\ one\ ton\ from\ source\ s\ to\ destination\ t.$

$supply_f \in \mathbb{R}^{+}$: Maximum possible supply from producer f (in tons).

through$_d \in \mathbb{R}^{+}$: Maximum possible flow through depot d (in tons).

$demand_c \in \mathbb{R}^{+}$: Demand for vaccines at customer c (in tons).

We have made several assumptions about the variables as shown in table 2. Our focus is on two major cost for this study. The first cost is the transportation cost from manufacturers to central hubs, registered providers and finally at-risk communities including the last mile component. We have assumed the cost per mile to be 1$/mile based on the estimates shared by city of Houston. The second cost is the penalty cost which shows the impact of shortages to these at-risk communities. For equal distribution, we have considered this amount to be $35, which was the cost two doses of Pfizer vaccine at the time of data collection. For prioritized distribution to at-risk communities, the penalty cost is $70 for at-risk communities which is double of $35 for other population. We have a total of 4 major vaccine hubs in Houston and 256 registered providers in 96 zip codes in Houston.

We have incorporated the service level in our model using the imputed shortage cost. In the equation, α value will be utilized for required service level in a particular region, which will be used to calculate the imputed shortage cost. The higher the service level, the higher the imputed shortage cost will be, which reflects the main focus on those regions with higher service levels to minimize the imputed shortage cost. The secondary objective is to reduce the overall cost which includes transportation cost and holding cost. We will use Mixed Integer Programming (MIP) for transportation cost along with Q,r Inventory Model to calculate the overall holding cost. We will use the outcome from GIS mapping and Community health Index to prioritize more vulnerable zones in that scenario, so that those who need the medicinal the most can get it on time.

4.5.3 Decision Variables

$flows_{s,t} \in \mathrm{N}^{+}$: Quantity of vaccines that is shipped from source s to destionation t

4.5.4 Objective Function

Cost: Minimize total shipping costs.

$$Minimize\ Z = \sum_{(s,t) \in Sets \times Sets} Cost_{s,t} * Flow_{s,t} + penalty_c * deficit_c$$

4.5.5 Constraints

Producer output: Flow of goods from a producer must respect maximum capacity.

$$\sum_{t \in Sets} Flow_{f,t} \leq Supply_f \qquad \forall_f \in Producers$$

Customer demand: Flow of goods must meet customer demand.

$$\sum_{S \in Sets} flow_{s,c} + deficit_c = demand_c \qquad \forall_c \in Customers$$

Depot flow: Flow into a depot equals flow out of the depot.

$$\sum_{s \in Sets} flow_{s,d} = \sum_{t \in Sets} flow_{d,t} \quad \forall_d \in Depots$$

Depot capacity: Flow into a depot must respect depot capacity.

$$\sum_{S \in Cities} flow_{s,d} \leq through_d \quad \forall_d \in Depots$$

Table 4-2: Description of different parameters

Tabs	Description	Unit	Input Information
supply	The manufacturer and how many vaccines they have	number of vaccines	How many vaccines available in Houston
through	The depots / Walgreens / CVS / providers and how many vaccines they can hold	number of vaccines	How much capacity we think per place
demand	The Zip Codes demand based on population	people	Zip Code demographic info (given before)
Penalty	The CHI index the higher the more your prioritize (can be based on case info)	unit less	Either Case Info or CHI
Cost	The distances from a provider, depot (Walgreens), to customer	miles	Google maps where there are distances

4.5.6 Scenarios

In order to us to find the impact of different supply and demand scenarios on service levels to at-risk communities and the overall costs, especially when demand is much higher than supply, we have created different scenarios, and we will use the data provided by Houston Health Department in our model to analyze and compare the output for each scenario. As listed below, we will run and analyze eight different scenarios for this study. The first four scenarios are considering equal distribution for all communities, and last four scenarios will prioritize underserved communities as highlighted by Community Health Index score for each region.

- Scenario 1: 25% Supply & 25% Capacity (at the time of data collection) vs 100% Demand - Equal Distribution
- Scenario 2: 50% Supply & 50% Capacity (at the time of data collection) vs 100% Demand - Equal Distribution
- Scenario 3: 75% Supply & 75% Capacity (at the time of data collection) vs 100% Demand - Equal Distribution
- Scenario 4: 100% Supply & 100% Capacity (at the time of data collection) vs 100% Demand - Equal Distribution

In the first scenario, the actual supply of the vaccine and capacity of the registered providers was far less than the actual demand (20% of Houston population) consisting of elderly population above 60 and healthcare workers. In second scenario, we doubled the actual supply of the vaccine and capacity of the registered providers to measure the performance variables. In third and fourth scenarios, we increased the supply and capacity by 3 times and 4 times to again measure the performance variables such as service levels and costs. As mentioned earlier, first four scenarios were used with equal distribution for all population without using CHI scores to prioritize underserved communities. The scenarios with prioritized distribution using CHI will be discussed in chapter 5.

4.6 Results and Discussion

The section below discusses geographical mapping of city of Houston using the CHI scores and COVID-19 information as input, followed by discussion on results of different scenarios using optimized supply chain model.

4.6.1 Geographical Mapping

Using the Modified Health Index and Social-Economic Index for each zip code in Houston to calculate the CHI score, as well as the data for total number of reported cases and deaths for COVID-19 and geographical information, we created a map that overlay COVID information by zip codes with vulnerable communities. As seen in the figure below, the darker region shows the zip codes which contain the census tract with higher CHI score.

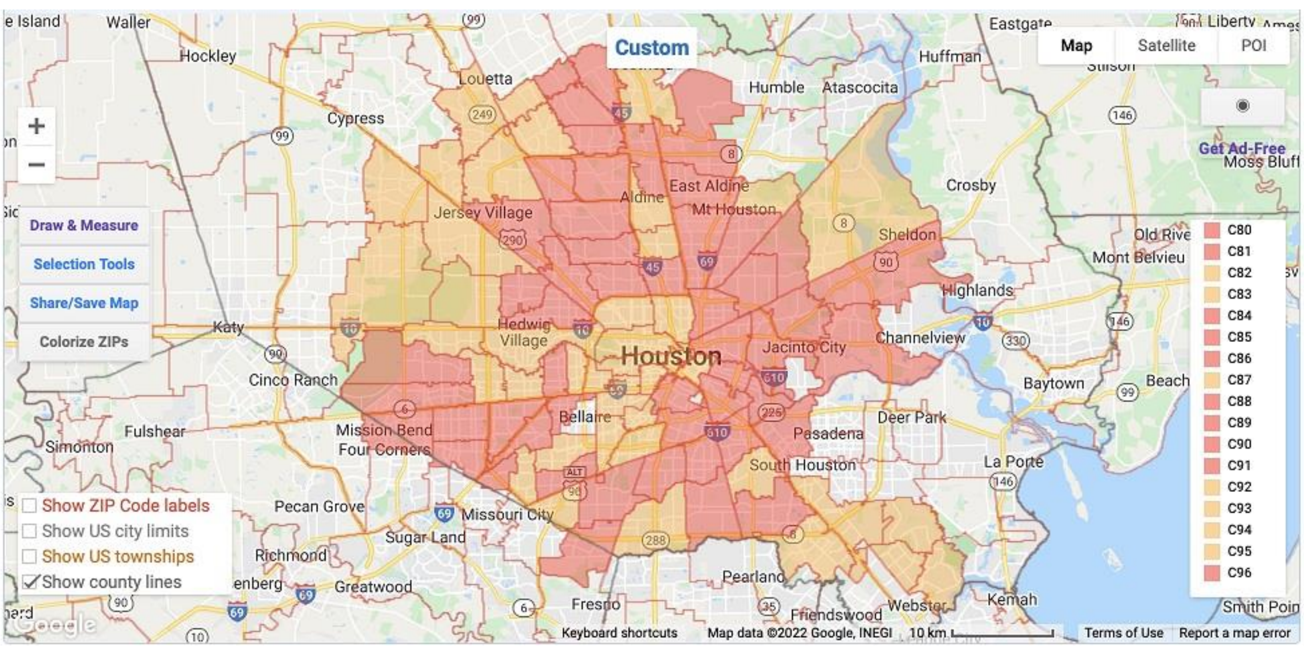


Figure 4-2: The map of city of Houston with all zip codes and Prioritized regions on the basis of zip codes

As discussed earlier, at the time of data collection, we were in phase I of COVID-19 vaccine distribution where demand was far higher than the supply of vaccines; we considered the elderly population and healthcare workers as the actual demand, which is 20% of the total population as per the collected data. The number of vaccination administration points, including hospitals, pharmacies and other locations at the time of data collection was 256 in Houston with 4 major central hubs in Houston providing vaccine shipments to these locations. All this information was used to create a new map along with 86 neighbourhoods as defined by city of Houston. The blue stars in below map shows the vaccine administration points (Hospitals, pharmacies etc.) closest to different neighbourhoods.

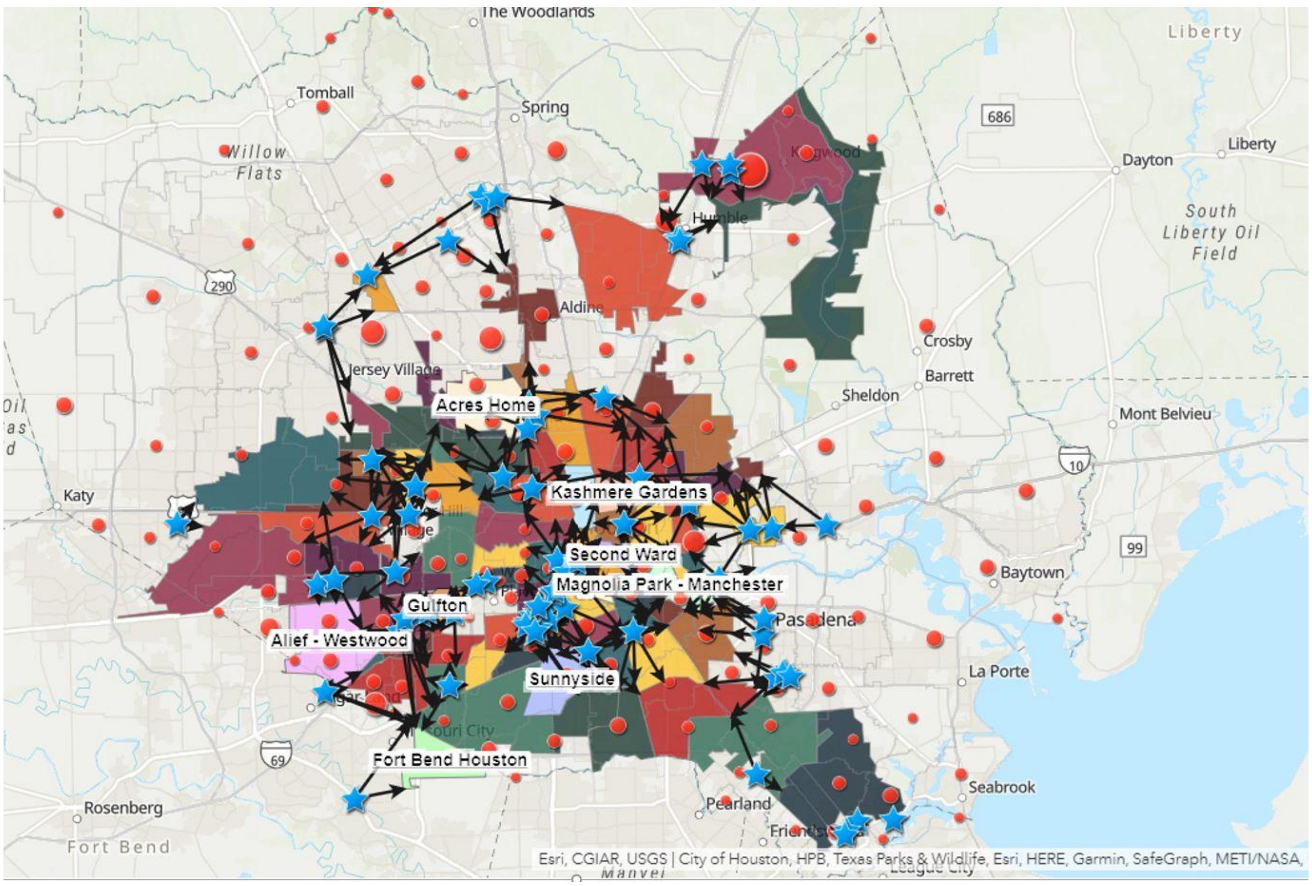


Figure 4-3: The map of city of Houston with 86 Neighborhoods and nearest hospitals

4.7 Results for different scenarios in Equal distribution

Using the data collected with the help of Houston Health Department, we ran our optimized supply chain model for the first four scenarios with equal distribution for all communities without prioritizing underserved communities using community health index (CHI). As described in methodology section, the actual supply of the vaccine and capacity of the registered providers is far less than the actual demand (20% of Houston population) consisting of elderly population above 60 and healthcare workers in the first scenario. In scenario 2-4, we increased the supply of vaccines and capacity of registered providers to measure the performance variables of different costs and service level.

4.7.1 Penalty Cost

From our supply chain model output given in below figures for all scenarios of equal distribution to all communities, we can see that in the penalty cost due to shortage is very high in scenario 1. This is because the demand is much higher and the supply of vaccines and capacity of registered providers of vaccines, this resulted in majority of the target population not provided with vaccines and leading to very higher penalty cost or imputed shortage cost. As we double the supply and capacity in second scenario, the penalty cost is reduced from 17.5 Million USD to 12.44 Million USD, but even then this penalty cost is on much higher side as still a huge number of target population are not provided with vaccine. As we keep on increasing the supply of vaccine and capacity of registered providers in scenario 3 and 4, the penalty cost keeps on reducing, until it reaches zero at scenario 4, which means that supply is equal, or more than the demand and all target population is served.

Cost

Table 4-3: Penalty costs for four different Equal distribution Scenarios

Type	25 % Supply & Capacity	50% Supply & Capacity	75% Supply & Capacity	100% supply & capacity
Penalty Cost(in Millions)	17.560	12.443	7.535	2.684

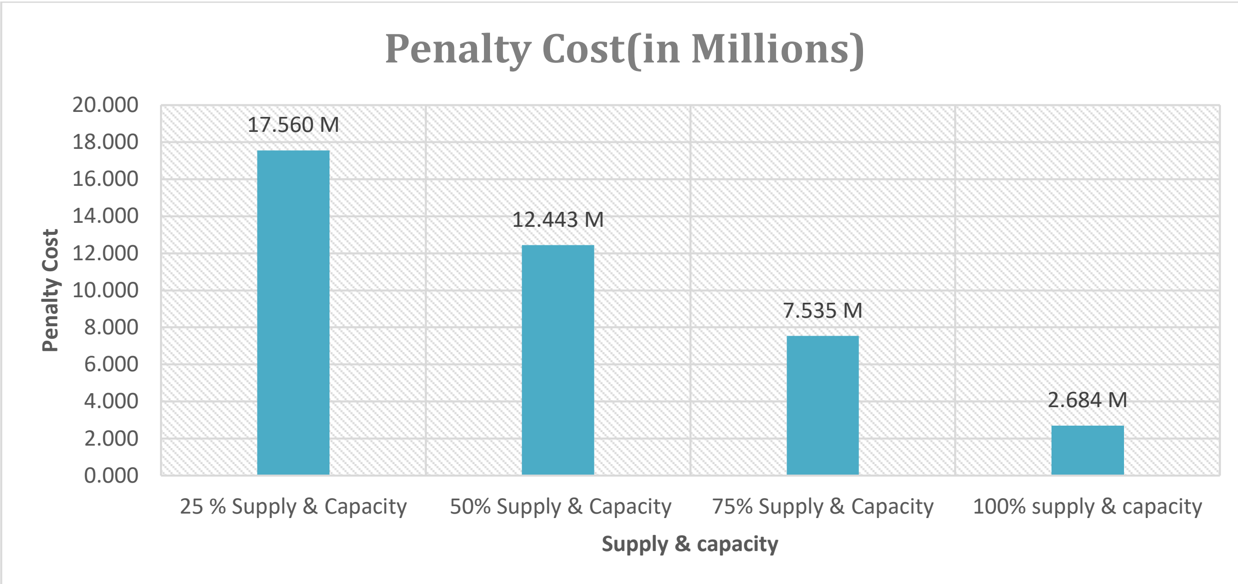


Figure 4-4: Penalty cost for four scenarios with equal distribution

4.7.2 <u>Transportation Cost</u>

Similarly, if we look at the transportation cost including the last mile from all major hubs to vaccines administration points (registered providers) to locations of target population, we observe that the transportation cost is relatively low for scenario one and as we keep on increasing supply of vaccines in scenario 2-4, it increases the transportation cost. This is because in scenario 1, majority of the people are not provided with vaccines due to vaccine shortage, so less miles of transportation are covered. As we cover more people in scenario 2-4, transportation cost increase and gets to maximum level at scenario 4, where all target population is covered. It is worth noting that the transportation cost is far lower than the penalty cost. This is because the primary focus of our study is to save lives of people by providing them with vaccines, and reducing overall cost is secondary objective by optimizing routes and allocating optimal inventory levels, so penalty cost is more significant for our study.

Table 4-4: Transportation Cost for four different Equal distribution Scenarios

Type	25 % Supply & Capacity	50% Supply & Capacity	75% Supply & Capacity	100% supply & capacity
Transportation Cost(in Millions)	1.811	3.512	5.112	6.930

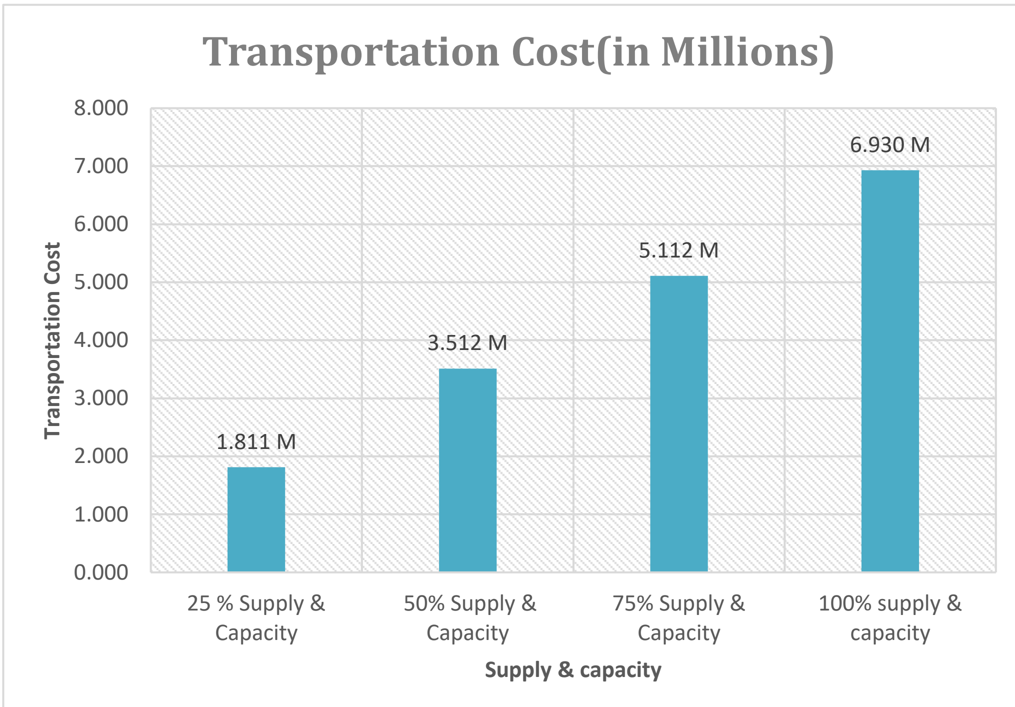


Figure 4-5: Transportation cost for four scenarios with equal distribution

4.7.3 Total Cost

Similarly, if we look at the total cost, we find out that as we reduce the shortages by increasing the supply of the vaccines, the total cost is significantly reduced as penalty costs have more significant and are drastically reduced by minimizing shortages.

Table 4-5: Total Cost for four different Equal distribution Scenarios

Type	25 % Supply & Capacity	50% Supply & Capacity	75% Supply & Capacity	100% supply & capacity
Total Cost(in Millions)	19.371	15.955	12.647	9.614

Table 4-6: Percentage of all Costs for four different Equal distribution Scenarios

Type	25 % Supply & Capacity	50% Supply & Capacity	75% Supply & Capacity	100% supply & capacity
Penalty	91%	78%	60%	28%
Transportation	9%	22%	40%	72%

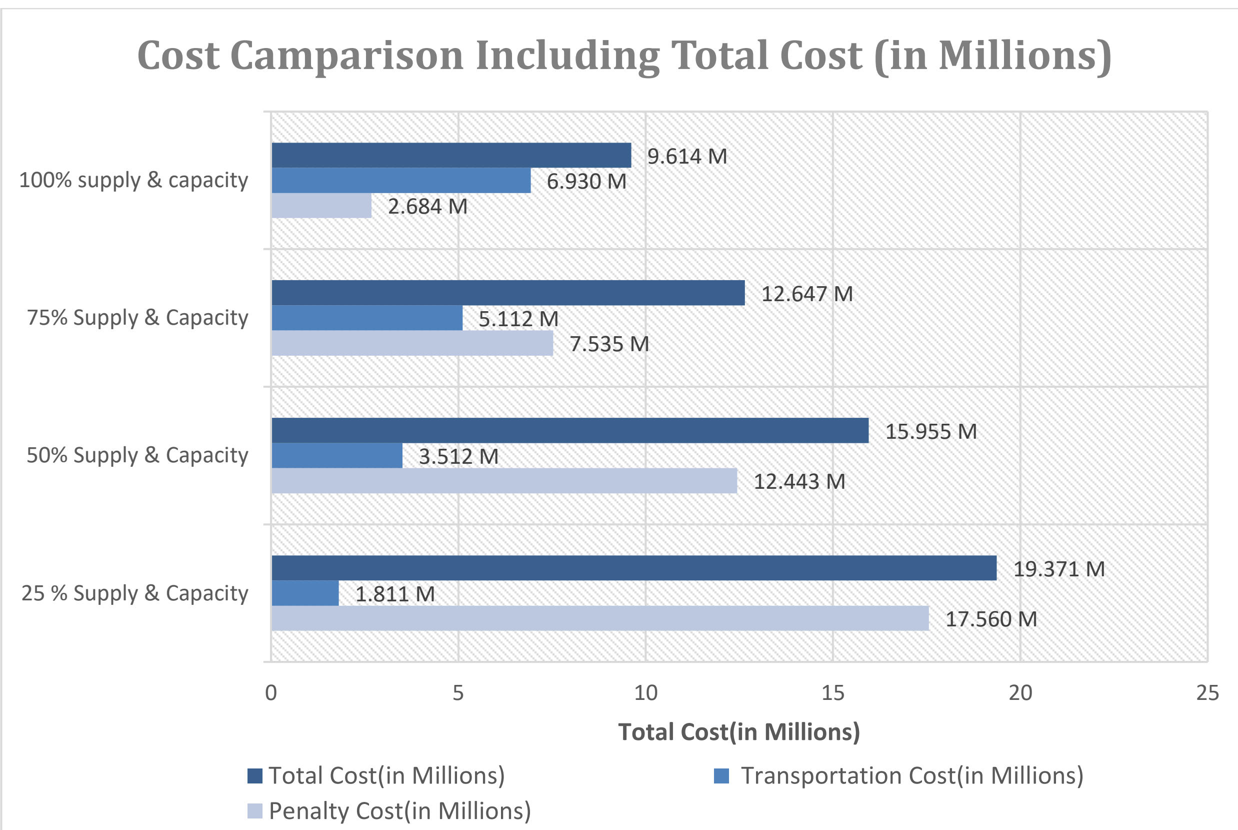


Figure 4-6: Cost comparison for four scenarios with equal distribution

4.7.4 Service Levels

The above cost analysis is echoed by the output of service levels as shown, in the figure below for equal distribution scenarios. In the first scenario, the service level is only 25.24%, which means that only 25% of the population is provided with the vaccine randomly. As we keep on increasing the supply of vaccines and capacity of registered providers from scenario 2-4, the service levels are increased and eventually reach 86.54% in scenario 4.

Table 4-7: Service Levels for four different Equal distribution Scenarios

Type	25 % Supply & Capacity	50% Supply & Capacity	75% Supply & Capacity	100% supply & capacity
Service Level	25.24%	46.05%	66.01%	86.54%

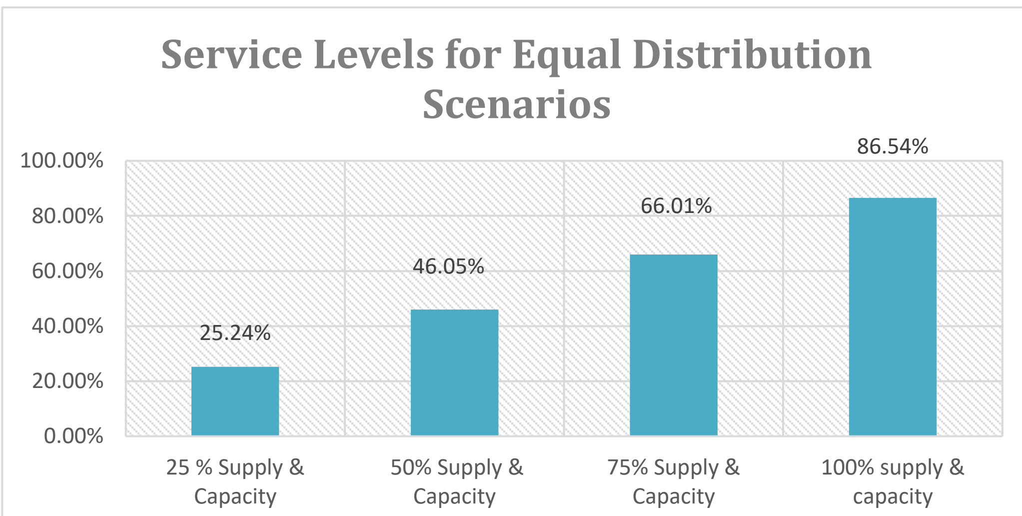


Figure 4-7: Service levels for four scenarios with equal distribution

4.7.5 Visual Demonstration for Distribution in four scenarios with equal distribution (without prioritization)

In this section, we will try to visualize how this model is distributing vaccines to different zip codes when we are running the model with equal distribution and without prioritizing the zip codes with at-risk communities. We will discuss the maps with prioritized distribution in next chapter.

The first map that we can see below is for scenario 1 for equal distribution. The green areas are those where the vaccine has been distributed. As the supply and capacity are only 25% of the actual demand, we already expect that not all areas will be supplied with vaccines in this scenario. Though it is interesting to notice that even though this model is optimizing cost by minimizing transportation costs and penalty costs, it is not prioritizing the regions that were highlighted in previous map with higher CHI scores. This is because in all equal distribution scenarios, we are keeping the penalty cost the same for all communities, hence no zip codes are prioritized on the basis of CHI scores and only focus in these scenarios is minimizing costs.

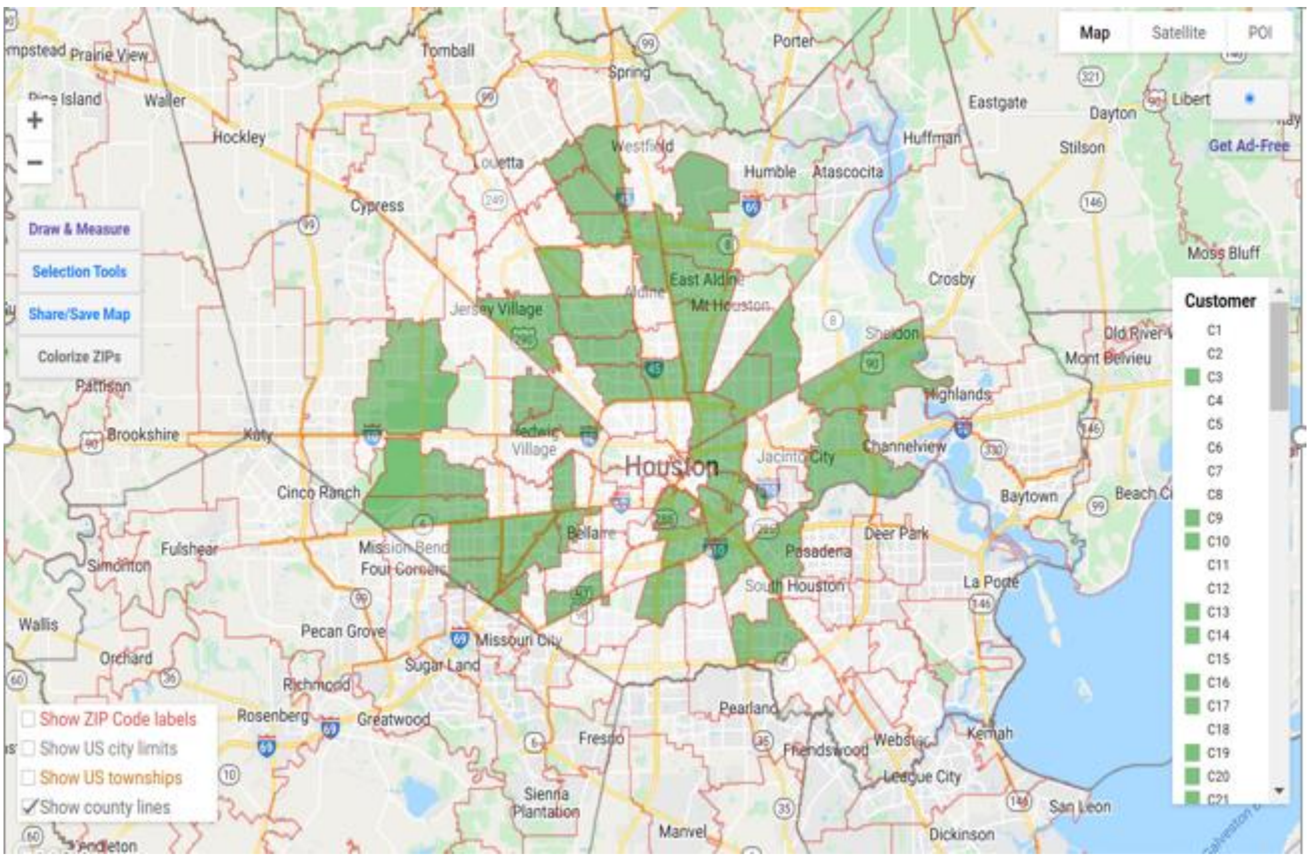


Figure 4-8: Distribution map for 25% Supply and 25% Capacity Scenario

As the supply and capacity is increased with respect to demand, more zip codes start to get green, meaning more zip codes receive vaccines. Again, since these are equal distribution scenarios, no zip codes get vaccines on priority basis.

Figure 4-9: Distribution map for 50% Supply and 50% Capacity Scenario

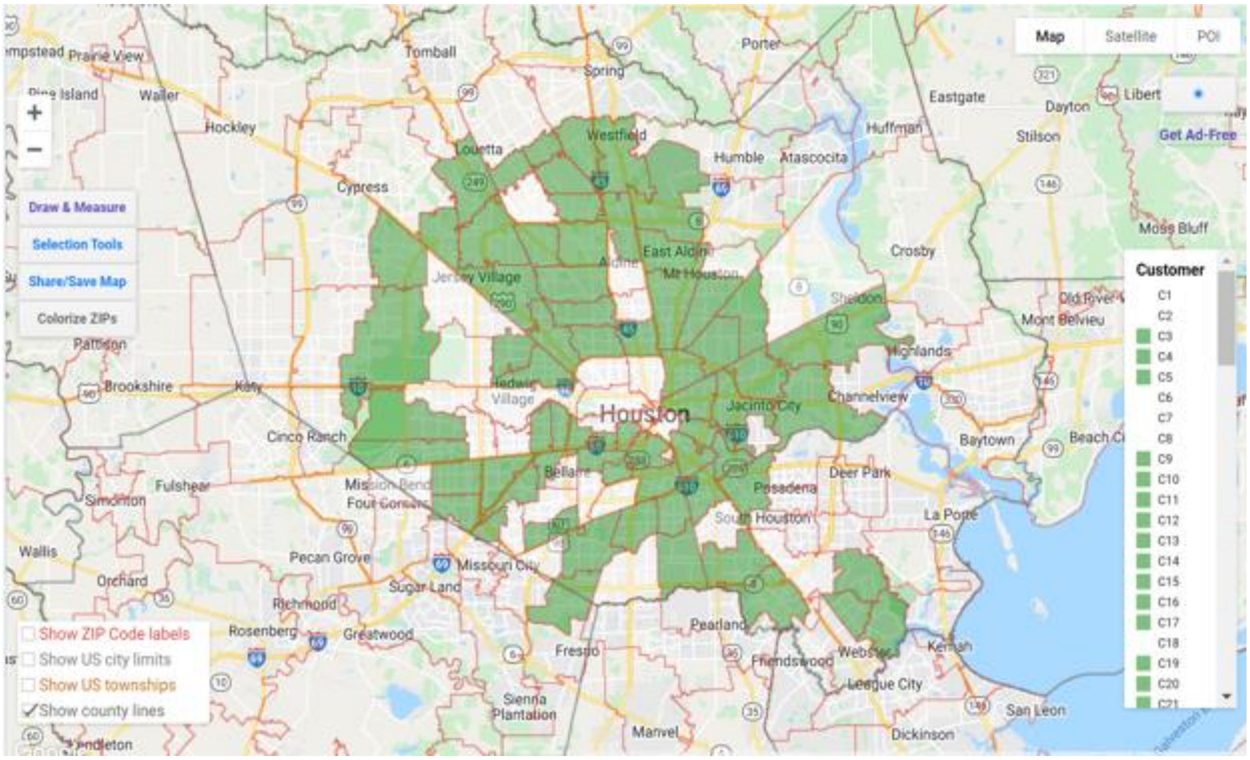


Figure 4-10: Distribution map for 75% Supply and 75% Capacity Scenario

Figure 4-11: Distribution map for 100% Supply and 100% Capacity Scenario

4.8 Conclusion:

After we have formulated the model and ran some basic supply and capacity scenarios with equal distribution (without CHI prioritization, we were able to see the variation in penalty cost, transportation cost, total cost and service levels. As we keep on increasing the supply and capacity vs demand in different scenarios, we can see that the penalty cost is dropping because more people have been provided the vaccine and hence less deficit. Similarly, the transportation cost is going up as we increase the supply and capacity vs demand, because more people have been provided with vaccines including last mile delivery to their addresses, hence the number of miles travelled is increasing, thus resulting in increased transportation costs. Lastly, we can see that the service level is increasing from 25% to 46% and eventually 86% as we keep on increasing the supply and capacity to meet the demand. In next chapter, we will run different supply and capacity scenarios vs demand with prioritized distribution using CHI, and will observe if the at-risk communities highlighted by high CHI score will get the vaccines on priority basis, even when the supply or capacity is not enough to meet with the demand.

Chapter 5: Readiness and Societal Cost Benefit Analysis of Optimized Supply Chain Model for At-risk Communities (Testing Scenarios with Prioritized Distribution)

5 Chapter 5: Readiness and Societal Cost Benefit Analysis of Optimized Supply Chain Model for At-risk Communities

In this chapter, we will assess the readiness and societal cost benefit analysis of optimized supply chain model for at-risk communities using different supply and capacity scenarios with respect to demand and also ensuring prioritized distribution for zip codes containing at-risk communities using CHI. Below is the list of scenarios, which were tested using optimized supply chain model for at-risk communities.

- Scenario 1: 25% Supply & 25% Capacity (at the time of data collection) vs 100% Demand - Prioritized Distribution
- Scenario 2: 50% Supply & 50% Capacity (at the time of data collection) vs 100% Demand - Prioritized Distribution
- Scenario 3: 75% Supply & 75% Capacity (at the time of data collection) vs 100% Demand - Prioritized Distribution
- Scenario 4: 100% Supply & 100% Capacity (at the time of data collection) vs 100% Demand - Prioritized Distribution

5.1 Results for different scenarios in prioritized distribution

In the previous section, we discussed the results of our supply chain model for equal distribution of therapeutics to all communities with four different scenarios of vaccine supply and providers' capacity to administer vaccine. In this section, we will discuss the results of prioritized distribution, using our CHI scores to prioritize underserved communities using our supply chain model. We will use imputed shortage cost or penalty cost and service levels as variables to prioritize these underserved communities in our model.

5.1.1 Penalty Cost

In figure 27, we can observe the same trend that we observed with equal distribution. The imputed shortage cost or penalty cost is very high in scenario 1 with current supply and capacity. As we increase the supply of vaccine and capacity of vaccine administration points or providers to match the demand from scenario 2-4, the penalty cost would increase drastically, eventually falling to zero in scenario 4 where supply is more than the demand. This figure for penalty cost for prioritized distribution looks similar to penalty cost chart for equal distribution in this case, but it is not always like that. The difference here is that the zip codes or neighborhoods that house underserved communities are prioritized here based on higher CHI scores and this drives our supply chain model to give higher service levels to these geographic regions of underserved communities. We will discuss this more when looking at service levels for prioritized distribution.

Table 5-1: Penalty costs for four different Priority distribution Scenarios

Type	100% supply & 100% capacity	75% supply & 75% capacity	50% supply & 50% capacity	25% supply & 25% capacity
Penalty Cost (in Millions)	2.325	6.825	13.099	24.537

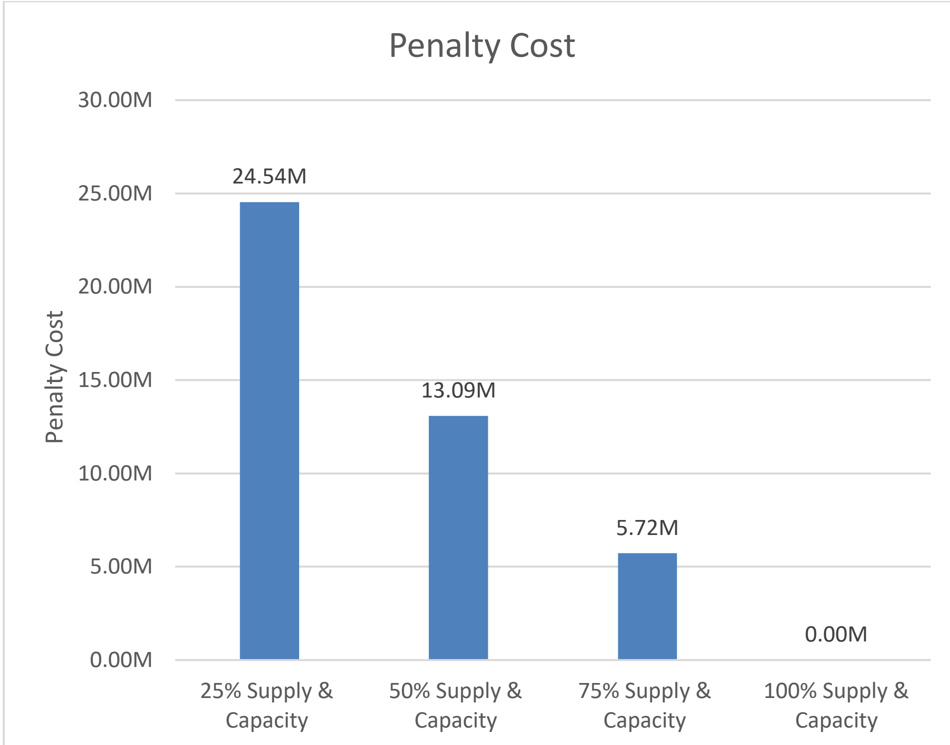


Figure 5-1: Penalty cost for four scenarios with prioritized distribution

5.1.2 <u>Transportation Cost</u>

Similarly, the same trend is observed for transportation cost. In scenario 1 where supply and capacity is much lower than the actual demand, the transportation cost is lower because a high ratio of target population is not provided with vaccine, so less miles covered from vaccine hub to hospitals to target population addresses (last mile). As the vaccine supply and capacity increases in scenario 2-4, more people are provided with therapeutics and hence higher transportation cost.

Table 5-2: Transportation costs for four different Priority distribution Scenarios

Type	100% supply & 100% capacity	75% supply & 75% capacity	50% supply & 50% capacity	25% supply & 25% capacity
Transportation Cost (in Millions)	7.434	6.389	5.393	2.557

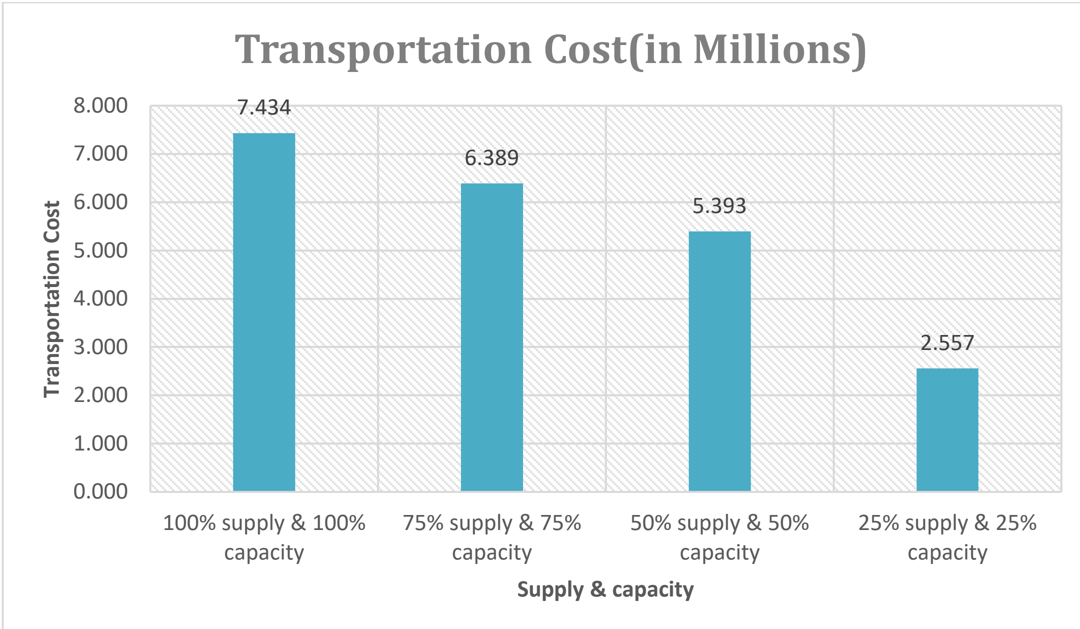


Figure 5-2: Transportation cost for four scenarios with prioritized distribution

5.1.3 Total Cost

Similarly, we can see that overall cost is reduced in case or prioritized distribution when the supply and capacity gets closer to the demand. The penalty cost is again more significant as compared to transportation cost as saving lives by ensuring timely vaccine delivery is primary objective.

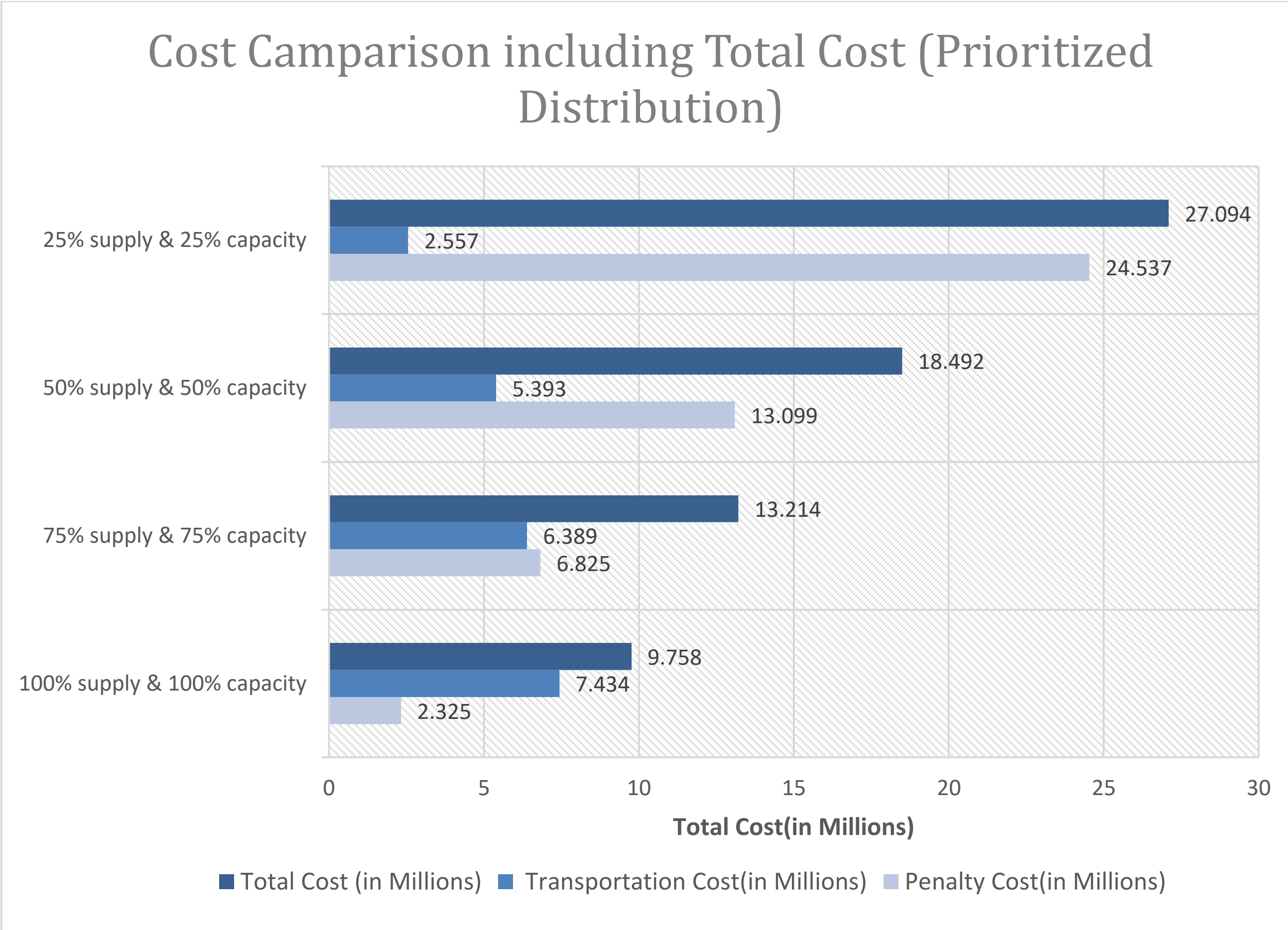


Figure 5-3: Cost comparison for four scenarios with prioritized distribution

Table 5-3: Total costs for four different Priority distribution Scenarios

Type	100% supply & 100% capacity	75% supply & 75% capacity	50% supply & 50% capacity	25% supply & 25% capacity
Total Cost (in Millions)	9.758	13.214	18.492	27.094

Table 5-4: Percentage of overall costs for four different Priority distribution Scenarios

% of total cost	100% supply & 100% capacity	75% supply & 75% capacity	50% supply & 50% capacity	25% supply & 25% capacity
Penalty	24%	52%	71%	91%
Transportation	76%	48%	29%	9%

5.1.4 Service Levels

Now, when we look at service levels for all scenarios for prioritized distribution, we observe that service levels increase when we increase the therapeutics supply and providers' capacity to match it with the demand.

Table 5-5: Service Levels for four different Priority distribution Scenarios

Type	100% supply & 100% capacity	75% supply & 75% capacity	50% supply & 50% capacity	25% supply & 25% capacity
Service Level	89.26%	68.88%	47.37%	23.76%

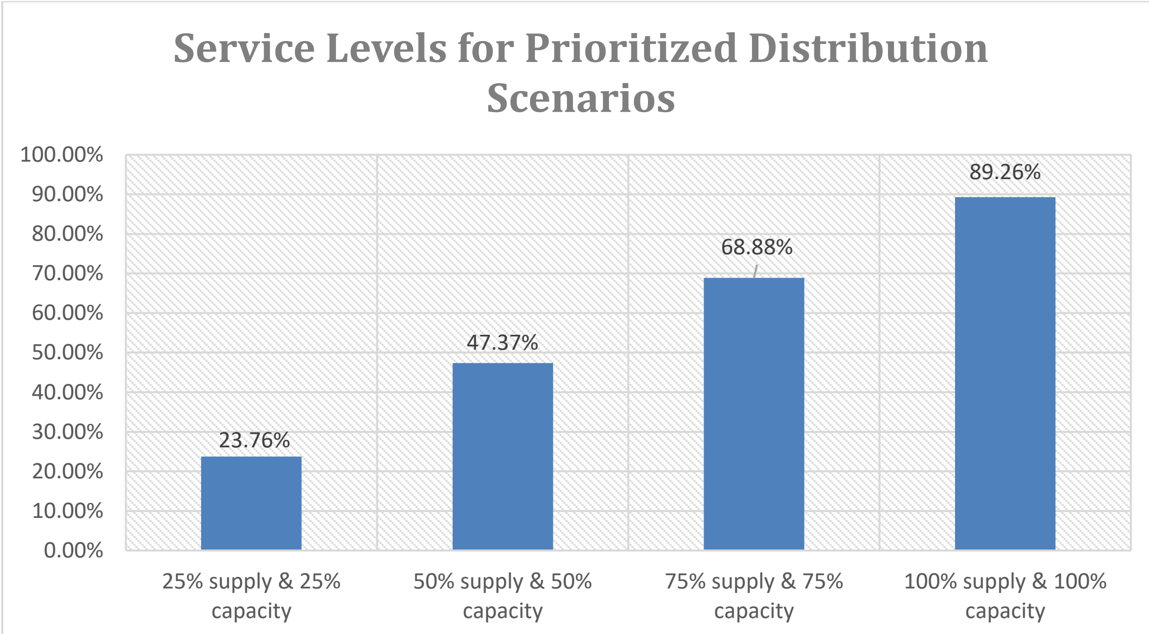


Figure 5-4: Service levels for four scenarios with prioritized distribution

It is very important to understand the difference between the service level for equal distribution and service levels for prioritized distribution. In case of equal distribution, we have a collective service level for entire population as we do not have any priority levels for any communities, but in case of prioritized distribution, the underserved communities get higher priority as compared to other communities. This means that even when the demand is much higher than the supply of therapeutics, as in the case of scenario 1, the prioritized underserved communities will have a very high service rate. To show this, we have run 16 scenarios given in below table.

Table 5-6: 16 different Priority distribution Scenarios to test different service levels

Sub scenarios	Supply	Capacity	Demand
1A	25%	25%	100%
2A	25%	50%	100%
3A	25%	75%	100%
4A	25%	100%	100%
5A	50%	25%	100%
6A	50%	50%	100%
7A	50%	75%	100%
8A	50%	100%	100%

9A	75%	25%	100%
10A	75%	50%	100%
11A	75%	75%	100%
12A	75%	100%	100%
13A	100%	25%	100%
14A	100%	50%	100%
15A	100%	75%	100%
16A	100%	100%	100%

Now running all these different scenarios using our model for prioritized distribution to at-risk communities, we get below results.

Table 5-7: Results of 16 different Priority distribution Scenarios with different service levels

Sub scenarios	Supply	Capacity	Demand	Average service level for Prioritized Zip codes	Average service level for Non-Prioritized Zip codes	Overall service level
1A	25%	25%	100%	42%	0%	24%
2A	25%	50%	100%	45%	0%	24%
3A	25%	75%	100%	46%	0%	25%
4A	25%	100%	100%	46%	0%	25%
5A	50%	25%	100%	44%	0%	24%
6A	50%	50%	100%	87%	0%	47%
7A	50%	75%	100%	83%	0%	45%
8A	50%	100%	100%	87%	0%	47%
9A	75%	25%	100%	44%	0%	24%
10A	75%	50%	100%	87%	0%	47%
11A	75%	75%	100%	100%	33%	69%
12A	75%	100%	100%	100%	46%	75%
13A	100%	25%	100%	44%	0%	24%
14A	100%	50%	100%	87%	0%	48%
15A	100%	75%	100%	100%	36%	71%
16A	100%	100%	100%	100%	77%	89%

As seen in table 5-7 above, with all different scenarios of supply and capacities in prioritized distribution, the vaccines will be distributed to at-risk communities on priority basis, resulting in much higher service levels, as compared to non-prioritized communities, and service level for at-risk communities in prioritized zip codes is much higher than overall service level. This means that underserved communities will get vaccine based on priority even when there is a shortage of vaccine due to high difference between supply and demand. The last mile element of our model will also make sure that the lifesaving therapeutics are actually provided to these at-risk populations. Below figures confirm the same with much higher service levels for prioritized zip codes as compared to non-prioritized zip codes and overall service levels.

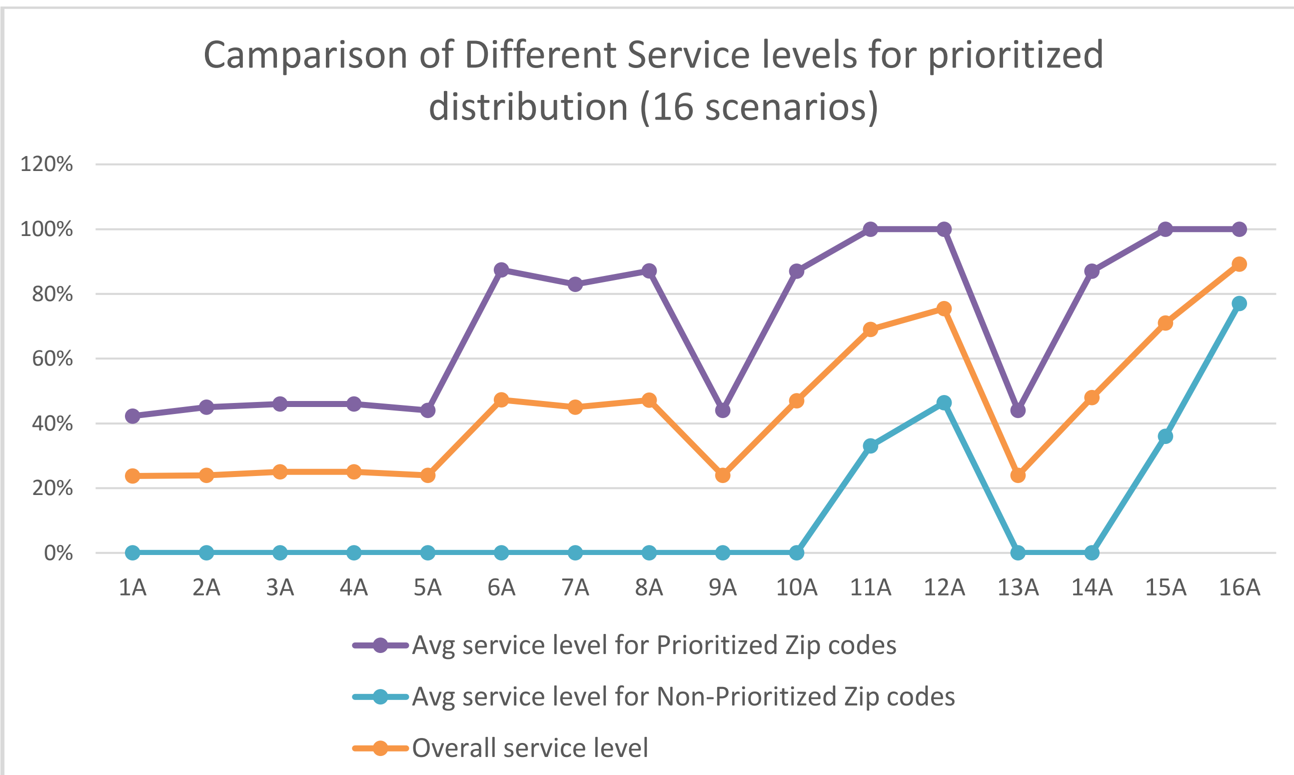


Figure 5-5: Comparison of Different Service levels for prioritized distribution (16 scenarios)

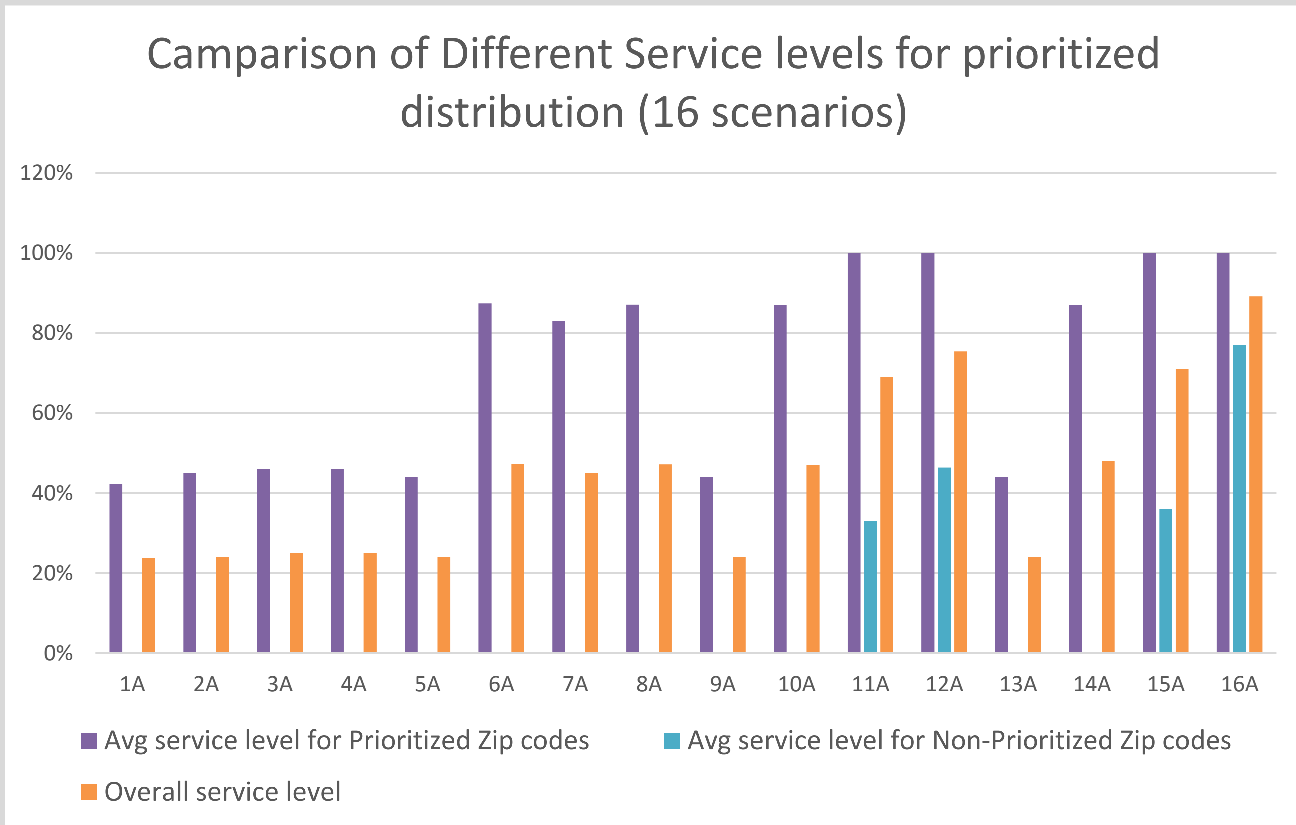


Figure 5-6: Comparison of Different Service levels for prioritized distribution (16 scenarios)

5.2 Visual Demonstration for Distribution in four scenarios with Prioritized distribution (Using CHI)

As seen in figure below, when the supply and capacity is much lower than the actual demand (25% supply vs capacity vs 100% demand), the vaccines will be first distributed to prioritized zip codes containing at-risk communities. As the supply and capacities increase to meet the demand, first the demand of at-risk communities will be filled and then for non-prioritized zip codes. The following figures show the same pattern.

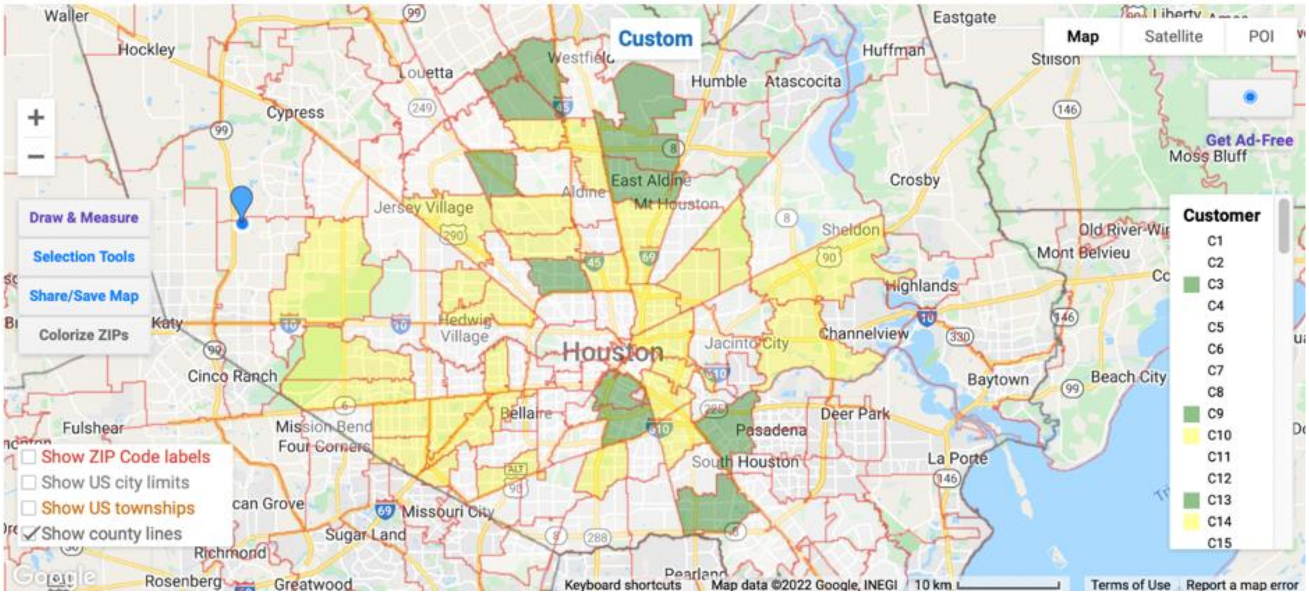


Figure 5-7: Distribution map for 25% Supply and 25% Capacity Scenario

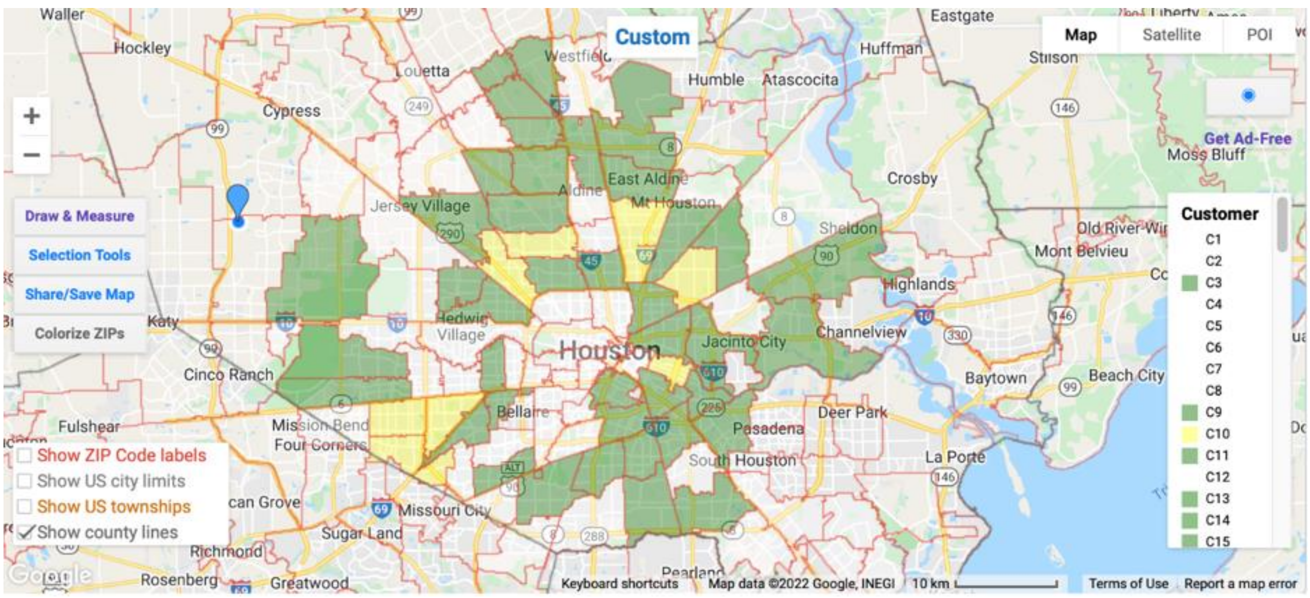


Figure 5-8: Distribution map for 50% Supply and 50% Capacity Scenario

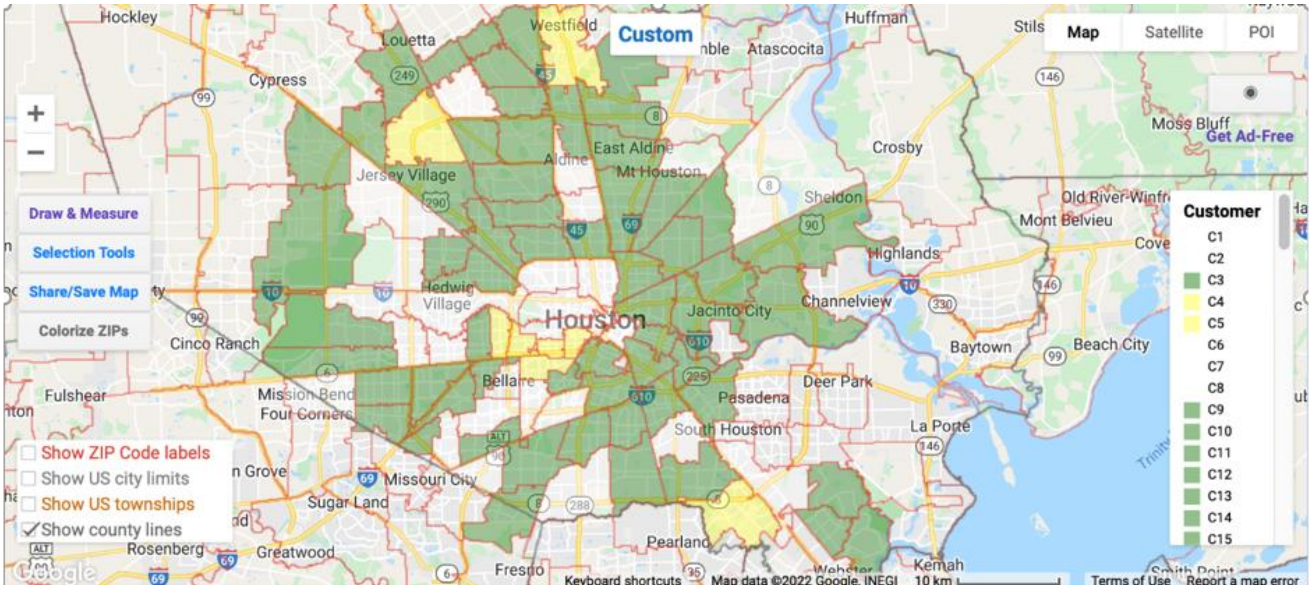


Figure 5-9: Distribution map for 75% Supply and 75% Capacity Scenario

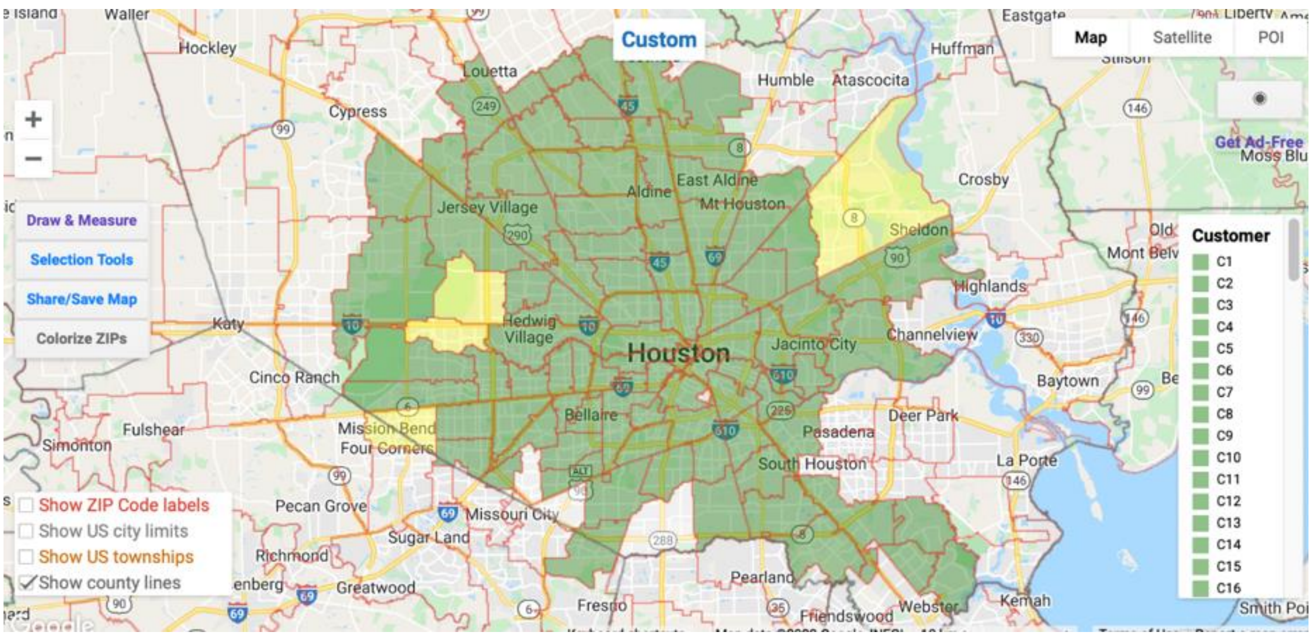


Figure 5-10: Distribution map for 100% Supply and 100% Capacity Scenario

5.3 Conclusion:

After running different supply and capacity scenarios vs demand with prioritized distribution, we have received the outputs and plotted these on maps as well. As we can observe that by using Community Health Index to prioritize at-risk communities, we are accurately ensuring that these at-risk communities get the vaccines on priority basis, even when the demand is much higher than the supply of vaccines and capacity of distribution points is not enough to meet the demand.

Now, as stated in chapter 1, we stated our hypothesis for service levels for prioritized distribution using our model as given below.

H_0: The Prioritized Supply Chain distribution model to underserved communities will results in higher service levels as compared to equal distribution model.

H_1: The Prioritized Supply Chain distribution model to underserved communities will not results in higher service levels as compared to equal distribution model.

Based on the outputs of the model (table 5-7, figure 5-5 and figure 5-6 and figure 5-7 to 5-10 with maps), we have observed that the service levels for zip codes at-risk communities have been much higher as compared to service levels for same zip codes using equal distribution. This is due to the fact that we used higher penalty costs for CHI prioritized zip codes in case of any deficit, so our optimization model automatically allocated vaccines to CHI prioritized zip codes on priority basis, even in scenarios where supply and capacity are much lower than the actual demand. This can also be observed by looking at the distribution maps for prioritized distribution vs equal distribution scenarios given below. Thus we reject *H1: The Prioritized Supply Chain distribution model to underserved communities will not results in higher service levels as compared to equal distribution model.* We are able to achieve our objective.

(The maps for both prioritized distribution and Equal Distribution Scenarios are given on next page).

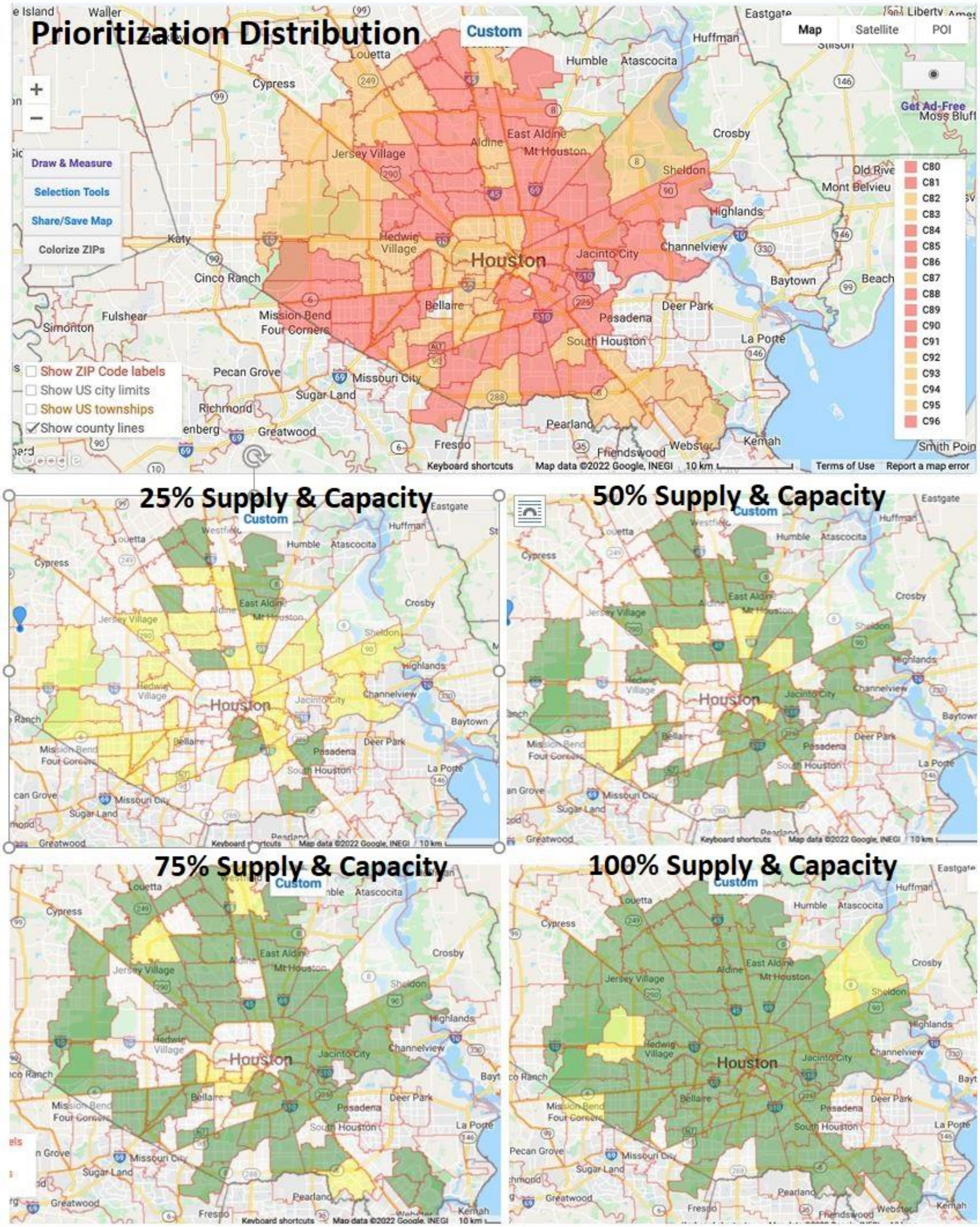


Figure 5-11: Comparison of different prioritized distribution scenarios vs CHI prioritized Zip codes

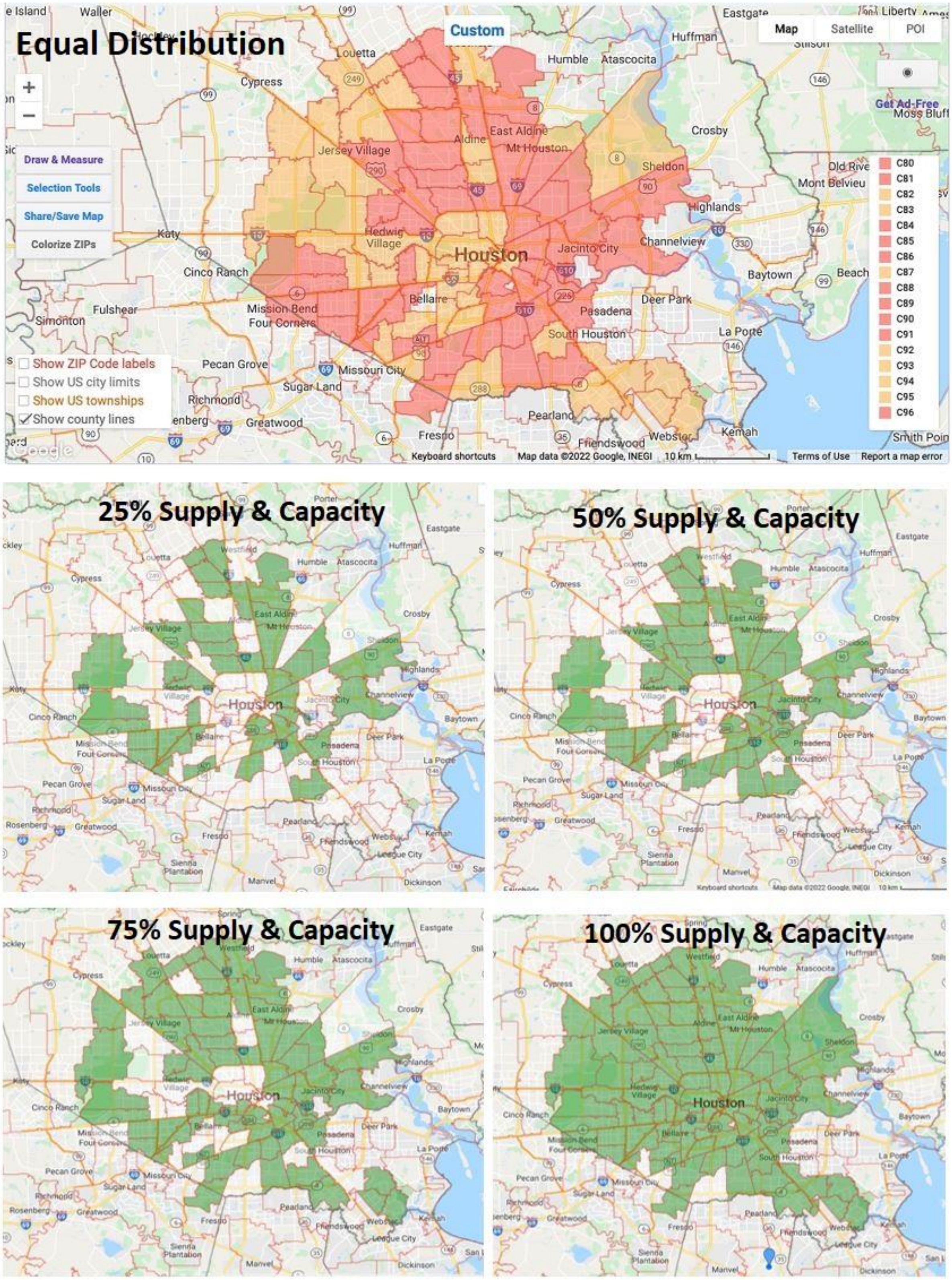


Figure 5-12: Comparison of different equal distribution scenarios vs CHI prioritized Zip codes

Similarly, we stated another hypothesis in chapter 1 about impact on overall cost when we adopt the prioritization model. The hypothesis is given below.

H_0: The Prioritized Supply Chain distribution model to underserved communities will results in significantly higher overall cost as compared to equal distribution model.

H_1: The Prioritized Supply Chain distribution model to underserved communities will not results in significantly higher overall cost as compared to equal distribution model.

Now, by comparing the final output costs for all scenarios for both prioritized distribution as well as equal distribution, we observe that for most of the scenarios, there is not significant difference in overall cost between equal distribution and prioritized distribution. Though it is noticeable that in case of 25% supply and 25% capacity vs 100% demand scenario in prioritized distribution, the penalty cost for is much higher (figure 5-12) as compared to 25% supply and 25% capacity vs 100% demand scenario in equal distribution. This is due to the fact that we doubled the penalty cost for zip codes which were identified as at-risk using CHI score, and in cases where supply is much lower than the demand, we expect the penalty cost to be much higher (due to doubling of penalty cost for at-risk communities for prioritization). As we increase the supply and capacity to meet demand in next scenarios, the overall cost for both prioritization distribution and equal distribution approximately becomes equal. Hence we reject the *H1: The Prioritized Supply Chain distribution model to underserved communities will not results in significantly higher overall cost as compared to equal distribution model.* Thus we have achieved the objective. We believe that by using this model, we can ensure that vaccines or other necessary therapeutics can be delivered to at-risk communities in a timely manner and on priority basis, even when there is shortage of vaccines. This model can be used by government and federal agencies to further devise strategies to ensure wellbeing of underserved minority communities. These insights can be used to model the COVID-19 Supply Chain which in turn can create a COVID-19 Community

Vulnerability Map that can inform at risk communities. The opportunity to understand through AI how communities are impacted by the COVID-19 pandemic and understand best practices for the community through simulations and case studies is novel. This is novel concept in that it does not focus on profit but on human life as the driver.

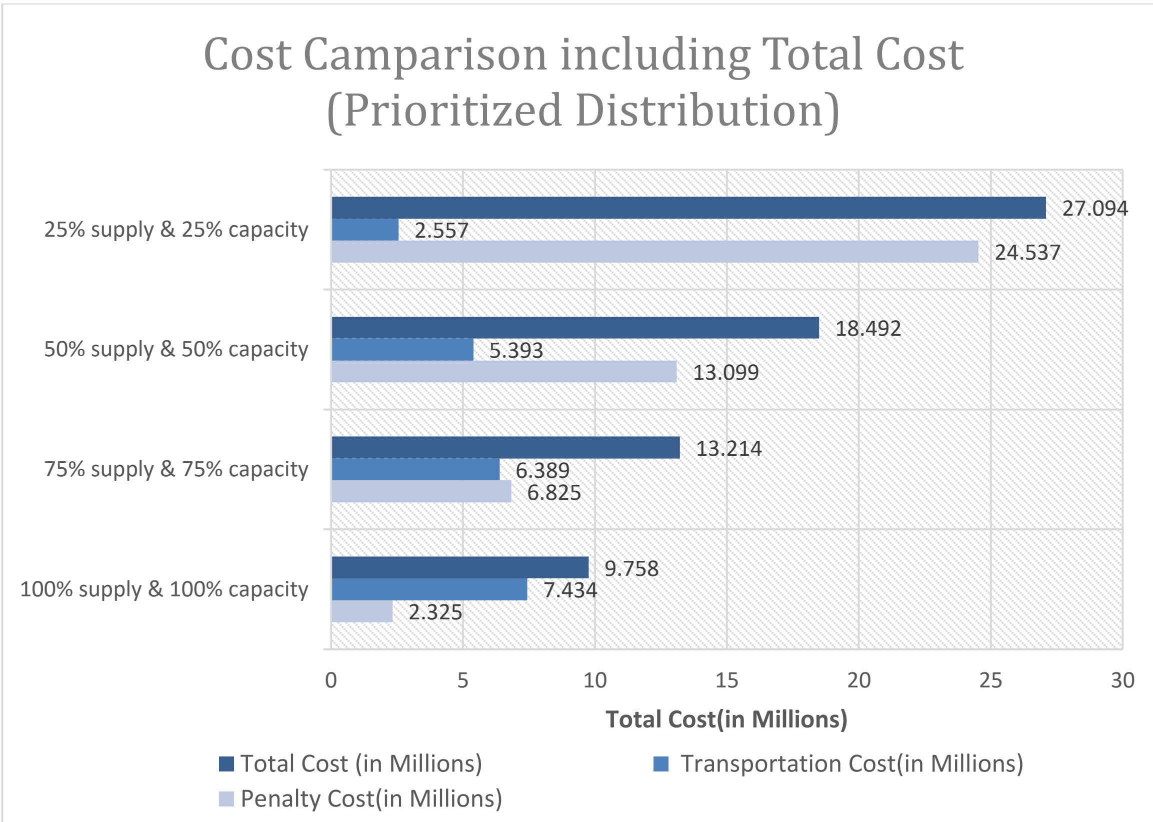


Figure 5-13: Cost comparison for four scenarios with prioritized distribution

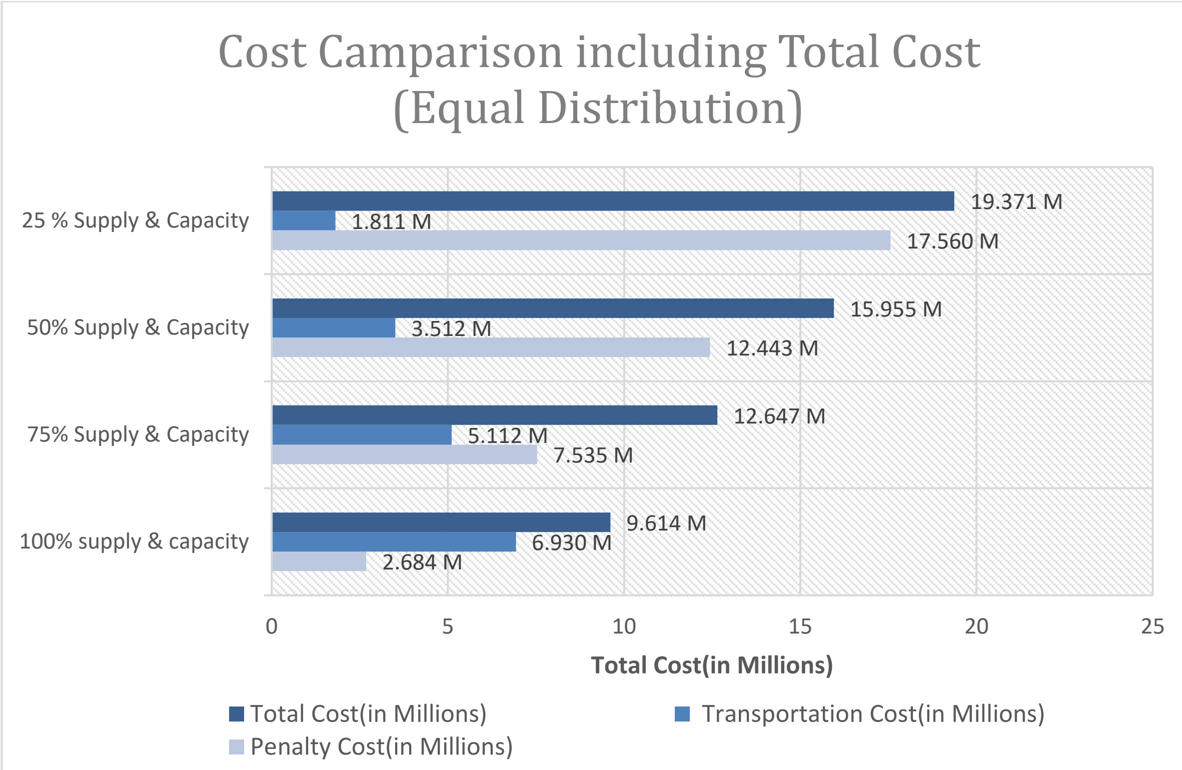


Figure 5-14: Cost comparison for four scenarios with prioritized distribution

6 Chapter 6: Conclusion

This research is based on a National Science Foundation funded grant (NSF Award Abstract # 2028612) to work on investigating supply chain strategies that would minimize the impact on underserved populations during pandemic. The underserved population could be at risk during the times of crisis, unless there is strong involvement from government agencies such as local and state Health departments and federal Centre for Disease Control (CDC). These government agencies were designed to help all communities but historically supporting underserved populations, because they do not have health insurance and their background. The COVID-19 pandemic was a crisis of different proportion, creating a different type of burden on government agencies. Vulnerable communities including the elderly populations and communities of color have been especially hard hit by this disease. The allocation and distribution of COVID-19 vaccines in a timely manner to these at-risk communities is important not only to end the pandemic but to do so equitably. There is a huge need for these agencies to change their strategies and supply chains to support all populations receiving therapeutics.

The research focused on making sure that underserved populations are not left out, especially considering the health disparities that exist. This project aimed to create a supply chain model that prioritizes geographic sections in the cities that house vulnerable communities. We collaborated with Houston Health & Human Services (HHS) to model supply chain for fourth largest city in US by using the concept of Community Health Index and COVID-19 Cases and geographical information to create a map that overlay COVID information by zip codes with vulnerable communities. The supply chain model then maximized social good by sending drugs or vaccines to the communities that need it the most regardless of ability to pay. The outcome of this study helped us prioritize the communities that need the vaccines the most. This informed our supply chain model to shift resources to these areas showing the value in real time prioritization of the COVID-19 supply chain. This research provides information, that can be used in our healthcare supply chain model to ensure timely delivery of therapeutics to underserved populations that are the most vulnerable and hence the overall impact of COVID-19 can be minimized.

The study identified the phenomena of last mile importance in achieving the objectives. The last mile transportation concept was critical in saving lives during the pandemic for underserved populations. Integrating the last mile concept along with an accessible healthcare index (CHI) allows for real-time strategies. The strategies were defined as mathematical models that could be used in real-time for these at-risk communities.

6.1 Future Work

For future work, this research can lead to collaborating with programs, such as Uber eats, Meals on Wheels, partnering with nurses to administer vaccinations to these populations. Data collected from the last mile of direct contact with members of at-risk communities to vaccinate or refusal to vaccinate will provide information to help predict which communities are not vaccinated due to access and which are vaccine hesitant. The responses from questionnaires about attitudes toward COVID vaccination and drug development will help future predictions of which vaccine hesitant communities are most likely to be persuaded to take the vaccine, increasing the efficiency of last mile efforts.

Utilizing automated data capture in conjunction with AI will allow the models to understand the risk drivers for the various forms of the COVID-19 viruses that can lead to acute respiratory illness, organ failure, and possibly death.

The broader impact of this research is that this research contributes research models to the AI, Data Science, and supply chain engineering fields that allow for provider and patient feedback from underserved and social economic disadvantaged communities to minimize the negative impact on these communities during a pandemic. This research also supports the importance of understanding the costs and nuisances of medical supply chains that can be mitigated through AI, Data Science, and public policy. Also, the impact on broadening participation of several domestic researchers from Underserved populations, specifically African Americans who are part of and can work specifically with these communities. The focus of this research in the identified underserved communities by a major health department supports that this research impacts the underserved populations in both computer science, engineering and social behaviors activities, a truly interdisciplinary and convergent research activities.

6.2 <u>Timeline of the study:</u>

Table 6-1: Timeline of the study

	Tasks/Specific Objectives	2020				2021				2022			
		Q 1	Q 2	Q 3	Q 4	Q 1	Q 2	Q 3	Q 4	Q 1	Q 2	Q 3	Q 4
1	*Project initiation. Kickoff meetings with Houston*												
2	*Identify the Automated Data capture and Artificial Intelligence needed to automate the COVID-19 Healthcare vaccine Supply Chain*												
3	*Modelling the vaccine Supply Chain from manufacture to home delivery that optimizes the most efficient manner to impact the most at risk populations*												
4	*Identify the readiness and the societal cost benefit of this model for use when medicinal become ready for the COVID-19 outbreak.*												
5	*Recommendations for implementation*												
6	*Dissertation Writing*												

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Below is the list of articles related to this dissertation, which have already been published in different journals.

[1] Jones, E.C., Azeem, G., Jones, E.C., Jefferson, F., Henry, M., Aboolmali, S., Sparks, J "Understanding the Last Mile Transportation Concept Impacting Underserved Global Communities to Save Lives During COVID-19 Pandemic", Front. Future Transp., 23 September 2021, No:- DOI: https://doi.org/10.3389/ffutr.2021.732331

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