INVESTIGATING THE IMPACT OF PANDEMIC SCENARIOS ON THE ANESTHESIOLOGY DEPARTMENT HEALTHCARE WORKERS AVAILABILITY: AN AGENT-BASED MODELING APPROACH

by

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ABSTRACT

SHWETA PRASAD. Exploring the Impact of Pandemic Scenarios on Healthcare Workforce Availability: An Agent-Based Modeling Approach.
(Under the direction of DR. VISHNUNARAYAN GIRISHAN PRABHU)

Protecting healthcare workers (HCWs) during a pandemic such as the one brought on by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is critical to provide timely medical care for patients. Although prior studies have investigated HCW unavailability during the pandemic and have developed policies such as double masking, rotating shift schedules, etc., none of the studies have modeled critical parameters such as varying patient census, vaccination rates, transmission rates, and multiple hospital locations. This research models a high-risk HCW group of perioperative staff, which includes anesthesiologists, nurse anesthetists, and nurses, to investigate the impact of segregating and rotating HCW staffing shifts in a large health system with multiple locations to address staff unavailability during the COVID-19 pandemic and prepare for potential future pandemics. Using the data from one of the largest health systems in South Carolina, we developed an agent-based simulation model with susceptible, exposed, infected, and recovery compartmental model to simulate various pandemic scenarios. Over 24 scenarios with different combinations of patient census, patient transmission rates, and vaccination rates were simulated while accounting for variables like geographic segregation, interpersonal contact limits, patient census, transmission rates, provider vaccination status, hospital capacity, incubation time, quarantine period, and patient-provider interactions to identify that policies that protect HCWs from getting infected.

Simulated findings indicate that restrictive policies and their rotation version of policies significantly (p-value < 0.01) reduced the peak weekly unavailability of HCWs by as much as 25%

when vaccination rates were lower (<75%). Moreover, these policies significantly (p-value < 0.01) reduced the percentage of HCWs getting infected over the simulation period by as much as 60% when vaccination rates were lower (<75%). However, the benefits of these policies diminished and were statistically insignificant when the vaccination rates increased to 90%. Observations from this research indicate the importance of modeling different parameters of a pandemic, such as vaccination rates, transmission rates, patient census, and other operational information, to develop targeted policies that protect HCWs during different pandemic stages. While the findings are based on the perioperative staff population, they can be implemented or considered while studying other high-risk groups. The simulation model can also be adjusted to simulate different hospital systems and future pandemics by manipulating the respective parameters to support future pandemic preparedness.

DEDICATION

I would like to dedicate this thesis to my beloved parents and sister. You are, Therefore I am.

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LIST OF ABBREVATIONS

HCW:	Healthcare workers
PPE:	Personal protective equipment
HFNC:	High-flow nasal cannula
NIV:	Non-invasive ventilation
ABM:	Agent-Based Modeling
ABMS:	Agent-Based Modeling and Simulation
GIS:	Geographic Information System
MBI:	Maslach Burnout Inventory
PTSD:	Post-Traumatic Stress Disorder
MILP:	Mixed-Integer Linear Programming
FRED:	Framework for Reconstructing Epidemic Dynamics
CDC:	Centers for Disease Control and Prevention
API:	Application Programming Interface
MATSim:	Multi-Agent Transport Simulation

CHAPTER 1: INTRODUCTION

The impact of COVID-19 on global populations has been profound and far-reaching. The pandemic has left an indelible mark on societies worldwide, from the loss of lives to widespread economic disruption. The economic fallout has resulted in job losses, business closures, and financial insecurity for countless individuals and families. Additionally, lockdowns, travel restrictions, and social distancing measures have altered daily routines and social interactions, contributing to widespread mental health challenges. Close to 14.9 million excess deaths were associated with the COVID-19 pandemic in 2020 and 2021, reinforcing the magnitude of the crisis (n.d.). As of the 20th of April 2022, the global confirmed cases of COVID-19 surged to more than 500 million patients (Moosavi et al., 2022).

While the impact of COVID-19 was profound across various industries, healthcare systems have been strained to their limits. Health systems faced several challenges, including shortages of beds and medical supplies and the unavailability of healthcare workers (HCWs), with immense burdens on their capacity to provide care. The prioritization of resources (personal protective equipment, masks, etc.) allocated to patients and the lack of PPEs due to supply chain challenges inflated the shortage of PPEs for frontline healthcare personnel. To worsen the scenario, the lack of vaccines during the initial outbreak and the high infectivity of the virus significantly impacted the HCW's availability to provide care. Elective surgeries were postponed/canceled, and these resources were allocated to the frontline. Furthermore, physicians from all specialties, retired physicians, and medical students were encouraged to join the healthcare industry due to the shortage of healthcare personnel.

While it is challenging to measure the actual risk associated with increased viral inocula, higher viral loads in patients who are very sick convey at least a hypothetical risk to medical professionals (Greenland et al. 2020). Studies on the transmission of SARS-CoV-2 from patients to healthcare personnel have been conducted; in these cases, infection management is crucial for safeguarding healthcare personnel and halting the spread of the virus (D. Wang et al., 2020). In addition to standard precautions, the World Health Organization guidelines advise healthcare providers to use droplet and contact precautions when caring for patients who have been confirmed or suspected to have SARS-CoV-2 infection.

Contact with infected surfaces and droplets/aerosol are the two main ways that COVID-19 is spread from person to person. If a person is exposed to high aerosol concentrations for an extended period of time in a somewhat enclosed space, aerosol propagation may also occur. Airborne precautions should also be used when performing any aerosol-generating procedure, such as suctioning, bronchoscopy, intubation, or cardiopulmonary resuscitation. (n.d.) Healthcare providers who treat patients with coronavirus disease 2019 (COVID-19) are more susceptible to catching the infection themselves. Particularly risky are aerosol-generating methods, including intubation, bag-mask ventilation, high-flow nasal cannula (HFNC), and non-invasive ventilation (NIV) (Tran et al., 2012). Airborne precautions are being used by many healthcare workers as an extra safety measure when caring for COVID-19 patients, according to frontline reports and additional guidance from groups in Hubei province (Wax & Christian, 2020).

Studies on the psychological effects of COVID-19 infection, the prevalence of the virus among healthcare workers, and the difficulties in providing healthcare have all been covered, but relatively few have concentrated on creating policies and plans to safeguard the workforce and lower the number of unavailability of healthcare workers. To support their research on better understanding how to mitigate the COVID-19 crisis, the authors have gathered information on a variety of strategies, including leadership, education, telemedicine, surge capacity planning, mathematical modeling, adjustable staffing algorithms, leadership, and ethical considerations. They assess these strategies' efficacy in light of previous pandemic experiences and offer doable suggestions for healthcare facilities that encounter staffing shortages in the event of a public health emergency. The research emphasizes the significance of putting safety precautions in place for healthcare personnel.

Healthcare personnel are particularly vulnerable to viral transmission from sick patients during intubation (odds ratio, 6.6), according to experience from the 2003 SARS pandemic (Tran et al., 2012). It should be highlighted, though, that a number of the medical professionals who became infected with SARS while performing intubations were merely donning standard surgical facemasks at the time of the procedure, and there is not much proof connecting intubation to an increased risk of virus transmission to medical personnel when appropriate airborne precautions are followed (Editorial I Anaesthesia and SARS, n.d.; Peng et al., 2020). Notably, while a number of post hoc reports from the 2003 SARS epidemic and newly emerging reports from the current epidemic advise using more advanced PPE—like powered air-purifying respirators, double gloves, coveralls, foot covers, or hoods—when conducting aerosol-generating procedures like intubation, there does not seem to be any proof that these precautions are better than more commonplace droplet, contact, and aerosol ones (Peng et al., 2020).

Medical workers made up 14% of the first 40,000 confirmed cases of coronavirus in Spain. 30% of the workers at the Igualada Hospital in Catalonia were placed in home isolation. Similar incidents have happened all around Europe (*Coronavirus in Europe: Thousands of Health Workers Out of Action - The New York Times*, n.d.). As of February 12, 2020, estimates from the Chinese Center for Disease Control indicate that over 3,000 healthcare workers had contracted the virus, despite significant attempts to stop its spread and reduce human-to-human transmission.1. Healthcare professionals are far more likely than the general public to contract COVID-19 (Chen et al., 2020).

Critical care and anesthesiology teams need to be ready for the arrival and ongoing care of patients infected with 2019-nCoV because there is a considerable probability that these patients will experience respiratory failure, necessitating critical care support. Due to their airway and ventilation management, anesthesiologists are perhaps significantly more at risk than medical professionals in other subspecialties. In the intensive care unit (ICU), they must tend to severely ill patients and provide perioperative care for patients undergoing urgent and emergency surgeries. They must also be close to the airway of patients during emergency airway intubation outside the operating theater. Although it is currently unknown how many anesthesiologists are affected, a handful of them have contracted the virus after performing tracheal intubation for confirmed COVID-19 patients. The operating room presents a risk of nosocomial infections to members of the perioperative team, including anesthesiologists, due to its hectic nature.

Understanding the virus's propagation and assessing its effects on healthcare systems were made possible in large part by modeling during the COVID-19 pandemic. To estimate crisis management strategies and predict transmission dynamics, a variety of modeling techniques were applied, such as Agent-Based Modeling (ABM). Specifically, ABM provided a potent tool to characterize individual behaviors and interactions within populations, revealing how these micro-level dynamics influenced macroscopic outcomes. Defined rules and behaviors for individual agents and tracking emergent patterns over time, agent-based modeling (ABM) enables researchers to simulate complex events. It was based on the concept of agents as computer entities with independent behavior. Because it can be difficult to depict using typical mathematical models alone, this method proved particularly helpful in conveying the complex social dynamics involving illness spread and healthcare solutions. Policymakers, medical experts, and researchers could gain a deeper understanding of the pandemic's intricacies and develop more efficient mitigation and response plans by utilizing ABM.

During the COVID-19 pandemic, various modeling approaches were vital for understanding the virus's propagation and evaluating its effects. Frontline healthcare personnel, such as doctors, nurses, and support staff, encountered hitherto unheard-of difficulties in coordinating patient care while lowering the risk of contracting the virus during the COVID-19 pandemic. Governments, medical facilities, and researchers used advanced methods like Agent-Based Modelling to study transmission dynamics as the virus spread worldwide, which helped them assess crisis management plans.

Agent metaphor fits perfectly well to the demands of complex and inherently distributed applications, where each agent is a coarse-grained computational system in its own right, as well as independently modifiable (Abar & Kinoshita, 2010). The earliest social agent-based model, in which people are represented by agents and socially relevant processes are represented by agent interactions, is credited to Thomas Schelling. Agent-based modeling (ABM) is a technique that makes it possible to mimic the individual behaviors of a variety of agents, monitor the results and behavior of the system over time, and explore system processes down to the level of their component parts (Crooks & Heppenstall, 2012). Fundamentally, ABM tools aid academics and practitioners in examining the ways in which the qualities, restrictions, and rules at the micro level affect a system's macroscopic behavior. As objects, agents are characterized by particular states and collections of useful characteristics, traits, or regulations; in other words, they have "behaviors" that can, under certain conditions, cause unique actions (Abar et al., 2017). When modeling complex phenomena, agent-based models are especially useful since they allow for the establishment of agency relationships between numerous agents or active entities with certain inherent features, which in turn allows for automated reasoning and problem-solving (Abar et al., 2017). When object-oriented ideas are applied, ABM is frequently a natural way to describe and simulate a system made up of real-world things (Gilbert & Terna, 2000). Among modeling methodologies, the agent-based approach is closer to "reality." Social theory, which is difficult to explain with mathematical formulas, can be represented and tested by agent-based simulations (Axelrod, 1997). By defining basic behavioral and transition rules linked to clearly defined entities, the models frequently map more readily to the problem's structure than equation-based models (Van Dyke Parunak et al., 1998).

Agents are capable of learning from their own experiences, acting on predetermined rules (such as heuristics), and interacting with the simulated world and other agents as well as themselves to inform their judgments. Three levels of communication between agents may arise from their interactions with one another: one-to-one, one-to-many, and one-to-place, in which one agent can affect other agents present in a specific location (Yousefi et al., 2018).

Libraries of predefined methods and functions are frequently used to support toolkits. These libraries can be seamlessly integrated into an agent-based model and connected with other software libraries, such as geographic information systems (GIS) like OpenMap or GeoTools. A toolkit can significantly cut down on the amount of time needed to develop the model, freeing up more time for study. Nevertheless, disadvantages include the need for the researcher to devote a significant amount of time to learning the programming language and how to create and apply a model in the toolkit. It is conceivable that the required feature will not be available after this time investment. Apart from toolkits, software for building agent-based models is becoming more and more accessible. AgentSheets and NetLogo are two notable examples. Using this software is especially helpful for quickly developing prototype or basic models. The main disadvantage of employing software is that it may limit researchers to the design framework it supports and make it impossible for them to modify or incorporate other tools.

The fact that agent-based models are frequently highly visual is very beneficial because, in terms of ABM, visualization is one of the best ways to convey important model information. Because ABM can explore systems with dynamic patient or health worker activity—a limitation of other differential equation or event-based simulation tools—its use in mapping health systems, for instance, has increased steadily over the past three decades. This makes ABM an essential tool for exploratory analysis.

Numerous fields, including healthcare, epidemiology, economics, and environmental science, have adopted agent-based modeling. ABM's capacity to mimic the actions of independent agents and depict intricate relationships among them renders it especially advantageous for comprehending dynamic systems and forecasting their consequences.

Modeling and simulation capabilities in healthcare systems have improved with the integration of ABM and machine learning (ML) approaches. With the use of machine learning algorithms, it is possible to glean insights from enormous datasets, spot trends and patterns, and create predictive models that project possible future events. By creating more precise and reliable models, researchers may examine many scenarios under different circumstances and analyze complicated healthcare dynamics in a more nuanced manner.

Our goal is to offer insights into the best staffing strategies for anesthesiology departments through a thorough study of simulation results and scenario-based modeling, supported by real-world data and knowledgeable advice from healthcare stakeholders. In order to create more robust and adaptable healthcare systems in the event of pandemics and public health catastrophes in the future, we work to contribute to the development of evidence-based decision-support systems for healthcare management.

In this work, we analyze the effect of staffing rules on the spread of COVID-19 among anesthesiology departments by utilizing ABM in conjunction with machine learning approaches. As frontline healthcare professionals, anesthesiologists encounter particular difficulties because of their intimate contact with patients during operations like airway management and intubation. We simulate various staffing strategies and assess their efficacy in limiting workforce disturbance, reducing the risk of infection transfer, and reducing the risk of mortality among healthcare providers by creating an agent-based simulation model.

This study is especially pertinent to agent-based modeling (ABM) since it provides a dynamic framework. The simulation of the complex interactions and behaviors of individual anesthesiologists in a healthcare setting confronting the COVID-19 epidemic is effective. Rather than treating all individuals equally, ABM considers their individual choices and activities. This enables researchers to observe how factors such as personnel levels, safety protocols, and patient interactions impact the virus's ability to spread within medical facilities.

In contrast to conventional models, ABM enables the modeling of a wide range of traits, actions, and decision-making procedures of independent agents—like anesthesiologists—within a complicated system. ABM offers a nuanced understanding of how staffing policies, infection control measures, and resource allocation strategies influence the spread of the virus and the capacity of healthcare providers to continue providing essential services by taking into account variables like contact patterns, patient interactions, and adherence to safety protocols. In order to prevent the spread of COVID-19 and maintain the resilience of healthcare systems in the face of unprecedented challenges, policymakers and healthcare administrators may make well-informed decisions with the help of this granular approach, which makes it easier to explore different scenarios and actions.

An efficient method for transferring management ideas through a mostly visual medium is agent-based modeling and simulation (Prabhu et al., 2020). Agents may represent organizations, individuals within institutions, or entire industry application processes. Agent-based modeling allows users to specify how objects and agents interact within their domain of interest. These models are then used to create user-generated real-world system models (Girishan Prabhu et al., 2022; Prabhu et al., 2023).

Methods, data sources, parameter values, simulation model structure, and scenarios taken into consideration are all covered in sections that make up the research. Along with offering insights into methods for reducing transmission risks and guaranteeing the safety of healthcare personnel, the study presents a thorough framework for examining the COVID-19 pandemic among anesthesiologists working in healthcare institutions.

The objective of the research is to comprehend the dynamics of virus transmission and the effects of multiple parameters on the spread of the virus among healthcare professionals. These elements include testing frequency, quarantine measures, immunity periods, and patient and colleague interactions. PRISMA Health Upstate and publicly accessible publications and literature on COVID-19 transmission probabilities, incubation periods, asymptomatic probability, recovery periods, and mortality rates are among the data sources. Clarity on the simulation setup is provided by the specific outlines of the model's parameters, values, and assumptions. The actual simulation model uses an agent-based methodology, considering every anesthesiologist as a distinct agent with particular characteristics and constraints. It was constructed using AnyLogic.

Based on contact rates and transmission probabilities, the model simulates interactions between anesthesiologists inside healthcare facilities and tracks each physician's status (vulnerable, exposed, infected, recovered). The simulation includes a number of scenarios, such as varying patient transmission rates and anesthesiologist immunity periods. It also takes into consideration the procedures for testing, the length of quarantine, and the potential for immunity or reinfection following recovery. To promote clarity and comprehension of the simulation procedure, the model's architecture and techniques for imitating the spread of viruses among medical professionals are described in depth.

CHAPTER 2: LITERATURE REVIEW

The interaction of agents depends on past experiences, and the unprecedented nature of the pandemic lets the onus be on the continual adaptation of dynamic occurrences (Abar et al., 2017) an extensive selection of 85 ABMS software tools is reviewed, giving data about the kinds of agents that each tool may be able to utilize and meticulously pulling the finer points from the user manuals or documentation of each specific tool and its applicability in terms of basic features, attributes while contributing to the relative comparison among various tools. Based on the study, AnyLogic was deemed appropriate.

The COVID-19 pandemic has prompted research efforts to understand the dynamics of infectious disease spread and develop effective strategies for mitigating its impact on public health systems. In this context, integrating agent-based modeling (ABM) and machine learning (ML) techniques has emerged as a promising approach for analyzing complex healthcare systems and informing evidence-based decision-making. This literature review provides an overview of recent studies that have utilized ABM and ML methodologies in the context of healthcare management during the COVID-19 pandemic.

Reports suggest that anesthesiologists have experienced high rates of burnout among themselves as a result of the enormous obstacles they have faced globally during the COVID-19 pandemic. Significant percentages of academic anesthesiologists in Pakistan have reported depersonalization, a decrease in personal accomplishments, and emotional exhaustion—all of which are major causes of burnout (Milenovic et al., 2020). This condition is not exclusive to Pakistan; research from other areas, such Zambia, also shows that anesthesia providers—especially nonphysician practitioners—have significant rates of burnout (Milenovic et al., 2020). Maslach Burnout Inventory (MBI) definitions of burnout include extreme tiredness, detachment and cynicism from the work, and a sense of failure and ineffectiveness, which suggests that burnout is a common problem in the field (Maslach & Leiter, 2016). These difficulties have been made worse by the COVID-19 outbreak; reports suggest that higher rates of PTSD are seen in nurses, particularly those working in anesthesia, as a result of prolonged workdays and ongoing exposure to the virus (Shaker Ardakani et al., 2023). Moreover, extensive modifications are now required to address concerns including work hour limitations, provider wellbeing, and safety issues as a result of the anesthesiology departments' reorganization in response to the pandemic, as seen at Montefiore Medical Center in New York City (Shaparin et al., 2021). The crisis has also brought attention to how critical it is for healthcare facilities to have an appropriate staffing level, where effective staff scheduling is essential to maintaining high standards of care and optimizing patient capacity (Cammer et al., 2014). The worldwide scope of the pandemic's impact on healthcare systems is highlighted by the similar problems that have been seen in other wealthy nations ((Faghanipour et al., 2020), (Sepulveda et al., 2020)). With their broad experience and multidisciplinary talents, anesthesiologists are well-positioned to take the lead in pandemic preparedness despite these obstacles, providing promise for successful adaptation to the changing healthcare delivery landscape (Shaparin et al., 2021), (Adams & Walls, 2020).

Effective management and control of medical center capacity during times of high demand may emerge as critical solutions in tackling the problems posed by pandemic epidemics. In order to maximize the number of cured patients, Burdett et al. (Burdett et al., 2017) investigate this further by using mixed-integer linear programming, in which various patient kinds are assigned to optimize resource allocation and hospital capacity. Subsequently, He et al. (He et al., 2019) offer an integrated nurse staffing-scheduling model that uses two-stage stochastic programming to reduce the risk of understaffing in the face of variable patient demand. This is followed by a model that authors in (Ordu et al., 2021) suggest that combines simulation and linear optimization in order to determine the necessary number of emergency beds, medical professionals, and nurses. In their article, Moosavi et al. (Moosavi et al., 2022) discuss the difficulty of staff scheduling in institutions during pandemics and stress the need to increase staffing levels. With an emphasis on reducing uncovered demand and staff preference violations, Guo and Bard (Milenovic et al., 2020) address the bi-objective staff scheduling problem utilizing a hybrid MILP formulation and column generating technology. Using a two-stage stochastic programming approach, Aydas et al. (Aydas et al., 2023) optimize staffing and adjustment costs by assessing short-term adjustment staff scheduling under demand uncertainty. Smet et al. (Maslach & Leiter, 2016) expand on this by introducing neighborhood search algorithms and constructive heuristics to reduce overall scheduling costs in a heterogeneous staff scheduling problem. A comparable staff scheduling problem is investigated by Hojati (Milenovic et al. 2020), who uses an iterative greedy algorithm to produce high-quality solutions. In health centers, Maenhout and Vanhoucke (Maenhout & Vanhoucke, 2013) combine scheduling and staffing decisions while taking the qualities of nurses into account. A dynamic program and MILP model are suggested by Lieder et al. (Lieder et al., 2015) to reduce task tardiness and earlyness penalties in residential care facilities. A stochastic programming model for staff scheduling in the face of unknown demand and patient lengths of stay is provided by Bagheri et al. (Bagheri et al., 2016) In addition, Güler and Geçici (Güler & Geçici, 2020) use mathematical programming to deal with the scheduling of doctor days off during pandemics, and Guerriero and Guido (Guerriero & Guido, 2022) provide integer programming models for staff scheduling during several pandemic scenarios, emphasizing different levels of flexibility. These studies provide a comprehensive framework that addresses staff scheduling issues during pandemics by utilizing a variety of mathematical and computational techniques to maximize resource allocation and operational effectiveness in healthcare facilities.

METHOLOGIES:

2.1. FRED framework and overcoming limitations

Studies have looked at the dynamics of influenza spread among urban populations, focusing on St. Petersburg, Russia. It models the spread of sickness using agent-based modeling, accounting for various contact patterns, workplace setups, and epidemic scenarios. It examines the effects of several population mixing assumptions on peak heights, epidemic curves, and outbreak lengths. (Leonenko et al., 2020)The researchers developed an Agent-Based Modeling (ABM) framework to address the issues with the existing models, particularly FRED. They first initialize the model by assigning a random status to each person's infectiousness and characterizing attributes like immunity. Individuals go about their daily lives, going to places where they might come into contact, such as homes, workplaces, or schools. Two elements that influence the transmission of an infection are infectiousness and contact rates. Infectivity varies over time in the disease dynamics model. Discrete time steps are employed in the Python-based simulations, which make use of Pandas and scipy.stats. Python and QGIS are used to analyze the instances' spatial distribution. Publications also discuss future research objectives, such as age-dependent contact rates and the initial infection spread. It provides insight into the challenges of influenza transmission in urban environments and the implications for public health interventions, in general.

2.2. Individual Space-Time Activity-based Model (ISTAM)

Simulations of the dynamics of an imaginary influenza outbreak in the Dutch city of Eemnes using the Individual Space-Time Activity-based Model (ISTAM) has been studied. (Yang et al., 2011)Work has been done to assess the efficacy of several CDC-recommended control methods, such as social distancing, closing schools, and instituting household quarantine, using intricate agent-based modeling. The best course of action, according to the results, is to impose a household quarantine, which considerably lowers the overall and peak number of cases while delaying the outbreak's peak day. On the other hand, closing schools on their own shows little effectiveness, as some illnesses are transferred to other locations. Mitigation tactics are more successful when control measures like home quarantine and school closure are combined. Sensitivity analyses show how the fundamental reproductive number (R0), alert values, and compliance levels affect the efficacy of control mechanisms. The work provides important insights for enhancing epidemic response techniques in urban areas, highlighting the significance of taking human behavior, real-world processes, and environmental elements into account when simulating disease transmission.

2.3. SIR model

With a focus on the Greater Toronto Area (GTA), the creation and application of a simulation model intended to comprehend the dynamics of disease distribution during a pandemic outbreak has been looked at. (Aleman et al., 2011) It highlights the difficulties in obtaining precise reproduction numbers (R0) and transmission rates for illnesses, which are necessary for modeling. In order to represent individual behaviors, interactions, and transitions between susceptible, infectious, and removed states, the model uses an agent-based simulation technique and adopts the Susceptible-Infectious-Removed (SIR) framework. Data from social-contact studies and census records, among other sources, are used to include factors impacting the transmission of diseases into the model. These factors include age-specific interactions, household sizes, commuting patterns, and transmission dynamics in public venues like hospitals and schools. The simulation takes into account both intimate and casual relationships, paying special emphasis to how public transportation affects the dynamics of urban transmission. It starts outbreaks and experiments with mitigation tactics, such as social distancing campaigns, evaluating their efficacy with GIS visualization and statistical analysis. Despite the inherent difficulties in validating pandemic models, the model's role in guiding government planning is emphasized, particularly for organizations such as the Ontario Agency for Health Protection and Promotion (OAHPP). It emphasizes the model's usefulness as a "what-if" tool for scenario comparisons and intervention assessments.

2.4. Measles SEIR Model

RepastS introduces ideas such as projection and context, in which projections form spatial relationships and the context include agents. The model integrates GIS for geographical modeling and enables simulation development and execution using the Repast Symphony toolkit and its Java APIs. A graphical user interface (GUI) allows for scenario creation and outcome analysis as agents interact within a physical world that is governed by predetermined rules and spatial relationships. This simulation employs the Measles SEIR Model with different settings and focuses on a portion of the population affected by a measles outbreak in Burnaby, British Columbia, Canada. (Perez & Dragicevic, 2009) Four scenarios clarify the dynamics of disease propagation by showing different ratios of susceptible to infected persons. Computational restrictions and data limitations for model validation are challenges. Sensitivity analysis guides model refining by identifying important parameters influencing outcomes. Based on sensitivity analysis results, the model realistically mimics disease outbreaks in urban areas and provides insights into the dynamics of dissemination. However, additional agent qualities and behaviors could be added in the future to enhance realism.

2.5. Age-stratified adjustment method

Age-stratified adjustment method discusses the problems in predicting case fatality rates (CFR) for COVID-19 in real-time, citing a number of factors, including age-related impacts, comorbidities, probable under-reporting, and the delay between confirmation and death. In order to overcome these difficulties, the study aims for more accurate CFR estimations by taking into account changes in known outcomes over time using an age-stratified adjustment method (de Noordhout et al., 2017). Taking into account that Diamond Princess passengers have an average age of 58 years, the study adjusts its estimations to match the age distribution in the Chinese outbreak, allowing for wider application. Although assumptions concerning the attribution of deaths and population comparability are recognized, several limitations are pointed out, such as possible variations in health conditions and healthcare accessibility between passengers on cruise ships and the mainstream population. Even though there aren't many deaths among those 70 years of age or older on the Diamond Princess, making age-specific CFRs impossible to produce, the studies emphasize how crucial it is to account for outcome delays and combine datasets from many sources in order to provide early insights regarding COVID-19 severity. In summary, albeit accepting certain limitations (e.g., demographic specificity, assumptions used), accounting for age differences and result delays is still essential to gaining meaningful insights into the COVID-19 fatality risk.

2.6. MATSim an agent-based transport simulation model

Research on this investigates how to describe and simulate the urban spread of influenza by combining transportation simulation and epidemiological modeling. It is predicated on a closed community with no demographic shifts and a constant probability of infection, wherein those who are affected carry on with their regular lives. Individual mobility and activities are modeled using equilibrium assumptions in the MATSim agent-based transport simulation. (Hackl & Dubernet, 2019)The model parameters are calibrated to replicate real-world traffic and infection data, with a special focus on seasonal influenza outbreaks in Switzerland. Activity schedules are obtained from empirical data. In simulations carried out for the Zurich metropolitan area, computational constraints limit the population size to 1% of the real population. In order to examine their effects on the spread of the epidemic, these simulations alter variables including initial infection rate, infection probability, and recovery probability. By comparing the model with the traditional SIR model and calculating model parameters based on observable data, studies have effectively recreated the influenza epidemic that struck Switzerland in 2016–2017. The epidemic spread model's simplicity and computing limitations are its main drawbacks, which point to future research topics that should include commuting patterns and demographic characteristics for better model realism and accuracy.

2.7. Susceptible-Exposed-Infectious-Removed-Treated- SEITR model

With an emphasis on the 2009 H1N1 outbreak in Kunming, China, the study creates an agent-based modeling (ABM) technique coupled with Geographic Information Systems (GIS) to simulate the transmission of influenza in urban environments. (J. Wang et al., n.d.)The model, which takes into account factors like cure rate, latent period, and transmission probability, represents the spatiotemporal dynamics of influenza transmission using Java programming and

Repast Simphony. Realistic urban environments provided by GIS data, such as population density layers and road networks, enhance the model. Hospitalized or confined individuals are represented by the "Treated" class in the SEITR extension of the SEIR model. While control measures like the quarantine ratio and duration to hospitalization are integrated to analyze their impact on disease spread, the multi-agent model simulates everyday activities and interactions. The model's accuracy is demonstrated by validation against H1N1 pandemic data, where simulation results closely resemble observed trends. An assessment of control measures indicates that early hospitalization and a quarantine rate more than 0.1 greatly reduce the risk of H1N1 transmission. This all-encompassing approach helps develop efficient preventive and control methods by providing insights into the dynamics of influenza.

Previous research has shown that several approaches can effectively reduce infections among healthcare workers and their unavailability; however, these studies have only been conducted in one small institution and do not take into consideration the ways in which different system elements interact to influence the spread of infections. The aim is to build a simulation model using the agent-based modelling (ABM) approach to gain in-depth insights into disease spread and determine the optimal staffing policy that minimizes infection spread and unavailability among the Healthcare workers.

In our approach to addressing infection control methods, we've incorporated crucial components. Among these, we've emphasized the importance of vaccination rates among healthcare workers (HCWs), recognizing that higher rates can significantly lower the spread of illnesses. Additionally, we've taken into account the rates of infection transmission at each facility. Assessing the quantity of interactions between healthcare workers and patients has been a focal point, as these encounters play a pivotal role in transmission dynamics. Moreover, we've recognized the significance of accounting for hospital patient censuses, understanding that fluctuations in patient counts can impact HCWs' workloads and exposure risks. By integrating these elements into our infection control policies, we've have hoped to propose an effective way to reduce the spread of illnesses.

CHAPTER 3: METHODS

3.1. Input Data

Data used in this study regarding bed capacity, locations, and perioperative HCWs required were derived from Prisma Health Upstate, which did not include any identifiers. The study was provided an Institutional Review Board (IRB) exemption by the Prisma Health IRB. The rest of the data used in the study were collected from publicly available epidemiologic data about COVID-19. We consider six different locations of Prisma Health Upstate and three different types of HCWs (anesthesiologists, anesthetists, and nurses) who are a part of the perioperative team. Among these, locations 1 - 4 are regular facilities receiving patients of all types, whereas two smaller locations were transitioned to treat only COVID-19 patients because of the surge experienced. There are 1167 beds available for patient care in total (facility 1: 700, facility 2,3,4: 108, and facility 5,6: 45), including inpatient beds and operating rooms. In our model, we did not specifically focus on the OR workflow. Instead, we focused on the inpatient beds and interactions out-of-the-OR activity (recovery room, workstation, etc.). The primary reason for this was that we assume that clinicians are masked and protected in the OR, whereas they might not be in the recovery room and workstation. We consider the number of interactions between each patient and each HCW type as a key factor in our ABM, which allows us to capture the impact of HCW availability on their workload in terms of patient interactions and the likelihood of getting infected. In our model, although we use a fixed transmission probability per interaction, the probability of an HCW getting infected is not static. We consider it as a function of total HCWs available to work, patient volume, and the average number of interactions with patients according to the following formula:

Patient-HCW contact rate = ((COVID-19 patient census * the average number of interactions required per patient)/ number of available HCWs).

Here, the COVID-19 patient census would vary based on the scenario under consideration (discussed in the next paragraph). The average number of interactions required per patient is based on the HCW type, where we assume nurses have more contact with patients than anesthetists. The number of HCWs represents the healthy workforce of each HCW available in the hospital. The motivation to use this equation here is to account for the varying HCW workload during a workforce shortage or surge in COVID-19 patients without detailed modeling of the complex workflow, which is significantly different for an operating room vs. an inpatient bed. Due to the lack of detailed data on the number of interactions required per patient with HCWs and the characterization of interactions among HCWs themselves in their workspace, we set these numbers in our experiments based on expert opinions from HCWs in the Prisma Health Department of Anesthesiology (see Table 1). Here, the number of interactions follows the CDC's guidelines for close contact, which is less than 6 feet away from a person for 15 minutes or more. The interactions between anesthesiologists represent their interactions in the recovery room, workstation, etc., and not while caring for patients. For nurses, their interactions represent their interactions in workstations and while passing by between inpatient beds. The number of interactions between anesthetists represents those outside the operating room. While it is possible that there might be no interaction between each HCW, we assume they could interact while passing by inpatient beds, workstations, lockers, or operating rooms. For the data on the testing frequency and quarantine period, we followed the policies and practices at Prisma Health during January 2022. The data pertinent to the COVID-19 transmission probabilities, incubation time, presymptomatic time, asymptomatic and symptomatic probability, recovery period, and mortality rate were obtained from publicly available Centers for Disease Control and Prevention (CDC) guidelines and literature from February 2022(*COVID-19 Pandemic Planning Scenarios | CDC*, n.d.). The possibility of reinfection was considered for HCWs returning to work after the mandatory quarantine since multiple studies reported such cases (*What Is COVID-19 Reinfection? | CDC*, n.d.) (Falsey et al., 2021). Finally, as represented in Table 1, the possibility of infection after vaccination was also considered, as prior studies observed that no vaccination provided 100% protection against COVID-19.

Although our model does not explicitly consider factors outside the hospital, to replicate the population dynamics, we consider three different scenarios for patient census represented by the percentage of hospital bed occupancy by COVID-19 patients at each facility: (i) low patient census (20-25%), (ii) medium patient census (45-50%), and (iii) high patient census (more than 80%). Additionally, we also consider two infection transmission rates: low and high transmission scenarios. Finally, we consider four scenarios where 0%, 50%, 75%, and 90% of HCWs' are vaccinated to evaluate the impact of vaccination rates. Although these combinations of factors (patient census, transmission rates, vaccination rates) do not come from actual scenarios at the partner hospital, the research team aimed to model and investigate these different scenarios to capture different population dynamics stages (early stage, peak infection, and recovery) for COVID-19 or similar pandemic. Table 1 below summarizes the key input parameters used for our model.

Table 1: Model parameters and values.

Parameters	**Values**

Provider transmission rate	4.0%
Patient transmission rate	0.04% or 0.004%
Incubation period	Triangular (2,4,12) days
Asymptomatic probability	40%
Quarantine period	5/10/14 based on vaccination
Mortality rate	1.8%
Reinfection Rate	0.0004%
Immunity period	60 days
Transmission rate after vaccination	12.5% of transmission rate
Providers and Patients vaccinated	0% or 50% OR 75% or 90%
Workforce testing frequency	1 per week
Patient Census	700-108-34 based on location
Number of interactions between providers per hour • Anesthesiologists and Anesthesiologists	3 per hour 1 per hour

• Anesthesiologists and Nurse Anesthetists/Nurses • Nurse Anesthetists and Nurses	3 per hour
Number of interactions between providers and patient • Anesthesiologists and patients • Nurse Anesthetists/Nurses and patients	 2 per patient 3 per patient

3.2. Simulation Model

In this paper, we created a simulation model in AnyLogic using agent-based modeling (ABM). This provided the flexibility to consider each anesthesiologist, nurse, and nurse anesthetist as a unique agent with specific parameters and attributes, interacting with other HCWs working in the same hospital. Additionally, this allowed the flexibility to model each hospital as an agent with further segregation into groups within each hospital. Moreover, the capability to track the current state (in terms of Susceptible-Exposed-Infected-Recovered, or SEIR) of each HCW made this the best option to model the rapidly spreading COVID-19.

Figure 1 depicts the state chart for each HCW, which illustrates the different states where an HCW can be at any given time. Before initiating the simulation, each agent is first scheduled to work at a specific hospital location for a week. Based on the policy under consideration, each HCW is assigned a list of HCWs with whom they can potentially interact within the hospital. By default, all HCWs start in the susceptible pool (assuming they are not infected). We employ two options to initiate infection among HCWs: a) through patient interactions or b) through interactions with other HCWs. If infected, instead of going directly into the state of being infectious, the HCW moves on first to the exposed state, where they stay for a certain period (referred to as the incubation period). In this exposed state, a provider is infected but not infectious, meaning they cannot spread the disease. Following the exposed state, they move on to the so-called presymptomatic phase, where they do not present any symptoms but are infectious, meaning they can potentially infect other HCWs. The symptomatic HCWs are tested immediately and follow appropriate quarantine protocols. The asymptomatic HCWs continue spreading the infection to other HCWs unless they test positive during the routine weekly testing, after which they follow the quarantine protocols. Following the quarantine procedures, there is a small probability that the HCW can expire, but most of them recover and enter the work system, where they can be reinfected based on the reinfection probability. A detailed process flow of different stages an HCW may progress through during the simulation can be seen below.

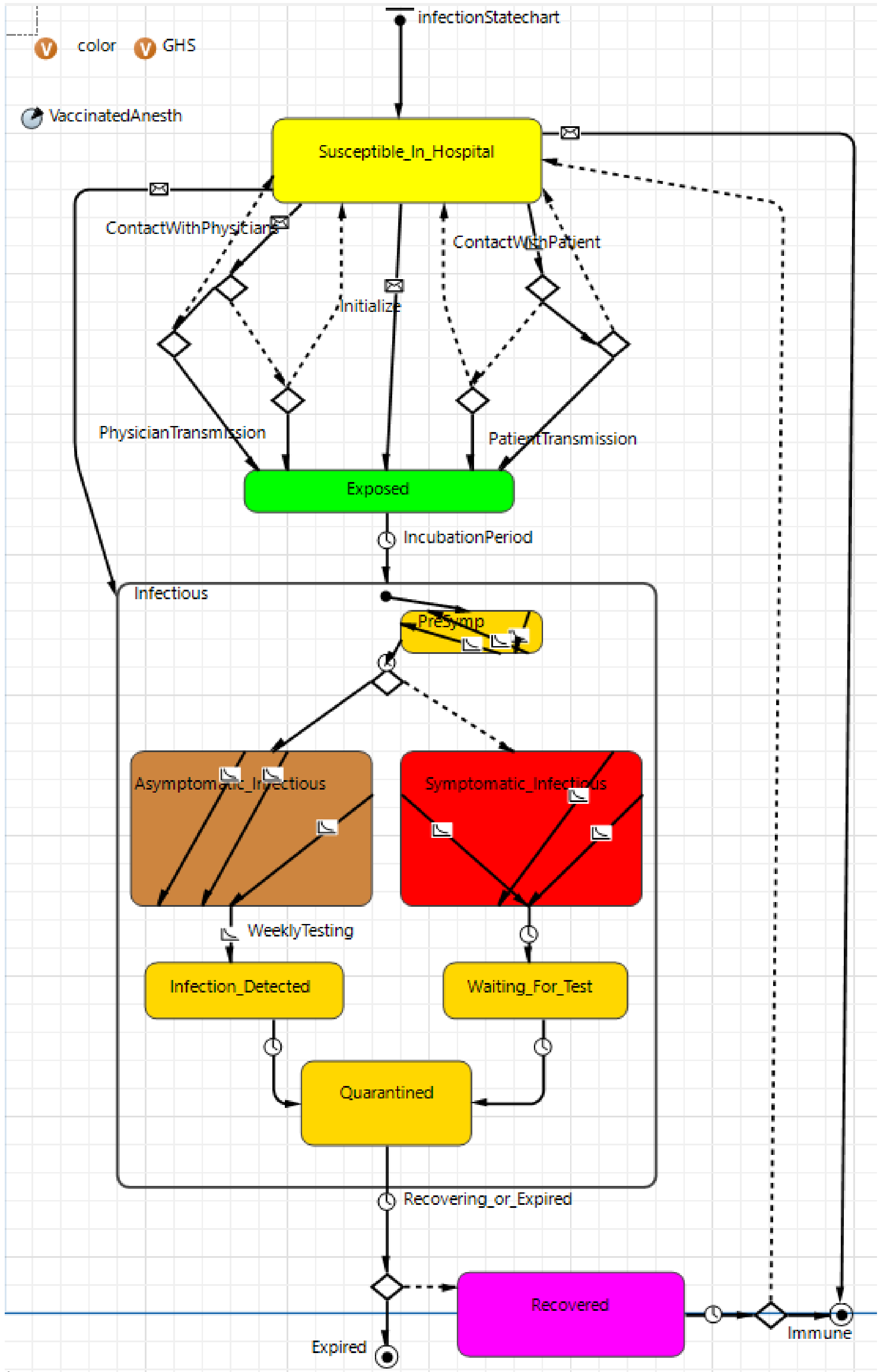

Figure 1: HCW state

From a modeling standpoint, on simulation initialization, each HCW is connected to a specific hospital, forming a bidirectional connection where each HCW is linked to a hospital, and each hospital is connected to a certain number of HCWs based on the hospital requirement. Further, within each hospital, we have groups that represent the various shifts available, as the HCWs will only interact with colleagues present during the same group. The HCW-to-HCW interaction is initiated by a separate hospital state chart message. Upon receiving the message from the HCW, the linked hospital will iterate and find other HCWs working on the same shift in the same hospital and forward the message to one of them based on the contact rate. Forwarding the message triggers the HCW state chart, and the HCW either transits to the exposed state or stays in the susceptible state based on the probability of transmission.

3.3. Simulated Policies

To identify the best staffing strategy that minimizes the number of infections and unavailability among HCWs, we compared six staffing policies under different scenarios of patient volume, vaccination status, and infection transmission rates. Based on expert opinions from the Department of Anesthesiology faculty at Prisma Health Upstate, we used the percentage of weekly availability of the HCWs and the total HCWs infected as the two primary performance metrics to compare various staffing policies. Specifically, we investigated six staffing policies with 3 primary policies and a fourth rotating policy integrated with the first three policies. Below, we provide the details regarding the six policies.

Policy 1 - Inter-Hospital Mixing (Baseline policy/Current Practice)

This policy corresponds to the current practice in the partner health system, where an HCW is allowed to work in any facility. Specifically, an HCW is assumed to have the option to switch facilities and/or groups every week but will work at the same facility each week. This policy allows the highest flexibility in staffing and scheduling. In our simulation model, the assignments of HCWs to facilities and groups are generated randomly.

Policy 2 - Inter-Group Mixing

In this policy, we first divide HCWs into groups and restrict the HCWs' interactions by restricting their shift options only to those available within a facility. Here, an HCW can switch groups within the same facility but cannot sign up for a shift in a different facility.

Policy 3 - No Mixing

In this policy, we further restrict the interactions among HCWs by segregating them into predefined groups within a single facility. They can only bid for a particular shift and stay with the same team throughout the simulation study horizon.

Policy 4,5,6 – Rotating Schedule

With these policies, we reduce the number of HCWs present in the hospital by implementing a rotation schedule. Specifically, at any given time, we assign 67% of the HCWs to work and the other 33% to stay at home, and these groups are rotated every two weeks. We combine this rotating policy with the aforementioned three policies, inter-hospital mixing, inter-group mixing, and no mixing, to obtain Policy 4, 5, and 6, respectively.

These policies were developed based on discussions with the providers at Prisma Health Upstate to ensure their realism and generality so that they can be adopted into any health system with multiple facilities. Specifically, based on discussions with expert clinicians working in perioperative settings, we used 22.5% of bed capacity as the low capacity, 47.5% as medium capacity, and 85% as a high capacity when COVID-19 patients occupied these beds. We evaluate the performance of different policies under multiple scenarios where we vary the patient census, vaccination status, and infection transmission probabilities. As mentioned earlier, these scenarios are not actual scenarios observed in the partner hospital. Instead, we consider various combinations of these factors as they allow us to differentiate between different types and sizes of healthcare facilities, reflect the impact of state/local policies, and model both high and low-risk geographical locations. Specifically, we tested the six staffing policies as detailed:

- Case 1: Low patient census & high patient transmission rate.
- Case 2: Med patient census & high patient transmission rate.
- Case 3: High patient census & high patient transmission rate.
- Case 4: Low patient census & low patient transmission rate.
- Case 5: Med patient census & low patient transmission rate.
- Case 6: High patient census & low patient transmission rate.

Two hundred replications of simulations were run for each combination of the parameters such that the reported metrics for the total number of infected HCWs was with a 99% confidence interval of +/- .1. A one-way ANOVA was utilized to compare if the total number of HCWs infected under each policy was statistically significantly different. In case of significant differences for the ANOVA, it was followed with a Tukey posthoc to identify the groups that varied statistically. For both statistical tests, an $\alpha = 0.05$ was used.

CHAPTER 4: RESULTS

This section summarizes the performances of the above six staffing policies across four vaccination levels, totaling 24 scenarios. Across each, the relative ratio of HCWs was 64.3% nurses, 27.46% nurse anesthetists, and 8.1% anesthesiologists. For ease of interpretation, we present the results across six cases and six policies at each vaccination rate, starting with 0% vaccination.

4.1. Zero Percent Vaccination

This policy corresponds to the early phase of the pandemic when no vaccines are available to prevent or reduce the spread of the virus. First, we investigate the percentage of HCWs infected over 90 days across various policies under each case, as seen in Table 2.

Table 2. Percentage of healthcare workers (HCWs) infected over 90 days at zero vaccination.

Cases	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	98.7±0.10	97.2±0.90	91.8±0.91*†	98.0±0.22	97.1±0.80	91.6±0.71*†
2	98.6±0.11	98.7±0.32	98.4±0.62	98.2±0.70	98.7±0.39	98.1±0.56
3	98.9±0.09	99.0±0.11	98.7±0.41	98.9±0.01	99.0±0.00	99.0±0.00
4	83.2±1.05	50.1±0.91*	26.1±1.10*†	83.0±1.10	50.1±0.87*	26.4±0.44*†

5	98.0±0.12	82.7±0.42*	59.4±0.01*†	98.3±0.62	81.7±0.66*	59.0±0.14*†
6	98.8±0.90	96.5±0.19	83.3±0.45*†	98.9±0.87	96.7±0.70	80.9±1.01*†

* = significantly different from policy 1,4

† = significantly different from policy 2,5

On performing an ANOVA, we observed that during high patient transmission cases (1-3), there were no statistically significant differences between the six policies (p-value > 0.05) except for one case (Case 1). For case 1, which is a low patient census scenario, we observed that policies 3 and 6, where HCWs are most restricted (no mixing), reported a significant reduction in the percentage of HCWs infected over the 90 days compared to policy 1 (p-value = 0.01), policy 2 (p-value = 0.02), policy 4 (p-value = 0.01), and policy 5 (p-value = 0.02).

For low patient transmission cases (4-6), we observed statistically significant differences (p-value < 0.05) in the total percentage of HCWs infected over 90 days. On performing a posthoc test, we observed that policies 3 and 6, where HCWs are most restricted (no mixing), reported a significant reduction in the percentage of HCWs infected over the 90 days compared to policy 1 (p-value < 0.01), policy 2 (p-value < 0.01), policy 4 (p-value < 0.01), and policy 5 (p-value < 0.01) across all low patient transmission cases (4-6). Additionally, we observed that the semi-restricted policy (inter-group mixing) and its rotation counterpart, i.e., policies 2 and 5, reported a significant (p-value < 0.05) reduction in the percentage of HCWs infected over 90 days compared to policy 1 and policy 4 (inter-hospital mixing) for cases 4 and 5. Finally, we observed that on comparing respective policies to their rotational counterparts, i.e., policy 1 vs. policy 4, policy 2 vs. policy 5, and policy 3 vs policy 6, we did not observe any statistically (p-value > 0.05) significant differences.

Next, we investigated the weekly unavailability of HCWs under each policy for different cases. However, given 6 cases (3 low patient transmission rates and 3 high patient transmission rates) for each vaccination rate, we present the values by averaging the 3 low and 3 high patient transmission rates. Table 3 below represents the average weekly unavailability of HCWs across three low patient transmission rates at zero vaccination rates.

Table 3. Average weekly healthcare worker (HCW) availability for low transmission rates.

Week	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	100%	100%	100%	100%	100%	100%
2	100%	100%	100%	100%	100%	100%
3	95%	97%	97%	98%	98%	99%
4	85%	90%	93%	89%	93%	95%
5	72%	81%	89%	72%	81%	89%
6	65%	77%	87%	62%	75%	86%

7	68%	79%	87%	65%	77%	85%
8	77%	83%	88%	74%	80%	86%
9	83%	85%	89%	83%	84%	89%
10	87%	87%	90%	87%	87%	90%
11	90%	90%	91%	90%	89%	91%
12	92%	92%	92%	93%	92%	92%
13	94%	93%	93%	94%	93%	93%

On investigating the peak unavailability of HCWs across the simulation period (90 days), we observed that no mixing (Policy 3) and its rotation version (Policy 6) outperformed other policies (Policy 1,2,4,5) by improving the weekly HCW availability by as much as 22%. Further, inter-group mixing (Policy 2) and its rotation version (Policy 5) outperformed inter-hospital mixing and its rotation version (Policy 1,4) by improving the weekly HCW availability by 13%. Figure 2 below represents the weekly availability of HCWs at a low patient transmission rate. Finally, comparing the rotation policies (Policy 4,5,6) to the respective restriction policies (Policy 1,2,3), the model predictions did not vary significantly regarding weekly provider unavailability.

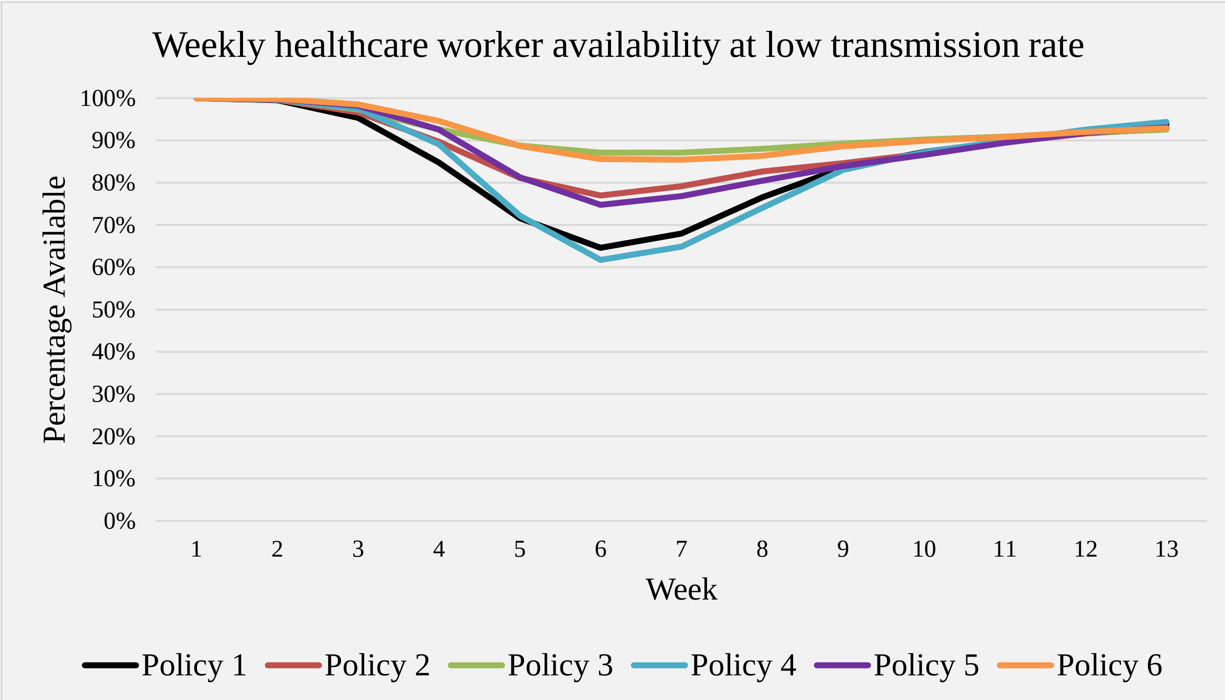

Figure 2: Average weekly healthcare worker (HCW) availability for low transmission rates.

On comparing the weekly unavailability of the HCWs under each policy during high patient transmission rates, no mixing (Policy 3) and its rotation version (Policy 6) outperformed other policies (Policy 1,2,4,5) by improving the weekly HCW availability by as much as 11%, as seen in Table 4 below. While not significant, the inter-group mixing (Policy 2) and its rotation version (Policy 5) outperformed the inter-hospital mixing and its rotation version (Policy 1,4) by improving the weekly HCW availability by 4%.

Table 4. Average weekly healthcare worker (HCW) availability for high transmission rates.

Week	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	100%	100%	100%	100%	100%	100%

2	97%	97%	97%	98%	98%	98%
3	79%	79%	83%	88%	88%	91%
4	54%	56%	64%	66%	67%	74%
5	47%	51%	57%	47%	51%	58%
6	60%	63%	65%	55%	59%	62%
7	77%	77%	77%	74%	74%	74%
8	88%	87%	85%	85%	85%	84%
9	94%	92%	90%	94%	92%	90%
10	96%	95%	93%	96%	95%	93%
11	97%	96%	94%	97%	96%	94%
12	98%	97%	95%	98%	97%	95%
13	98%	97%	96%	98%	97%	96%

Although the total percentage of healthcare workers infected over the simulation length (90 days) did not vary significantly across various policies during the high patient transmission rates scenarios except for one case, as noted in Table 4 above, we observed that the no mixing policies could reduce the peak unavailability of HCWs during a specific week. Moreover, at zero vaccination rates, we observed that the restriction policies could delay peak unavailability by a few weeks compared to the flexible policies (current practices). Figure 3 below represents the weekly availability of HCWs at a high patient transmission rate during zero vaccination rates.

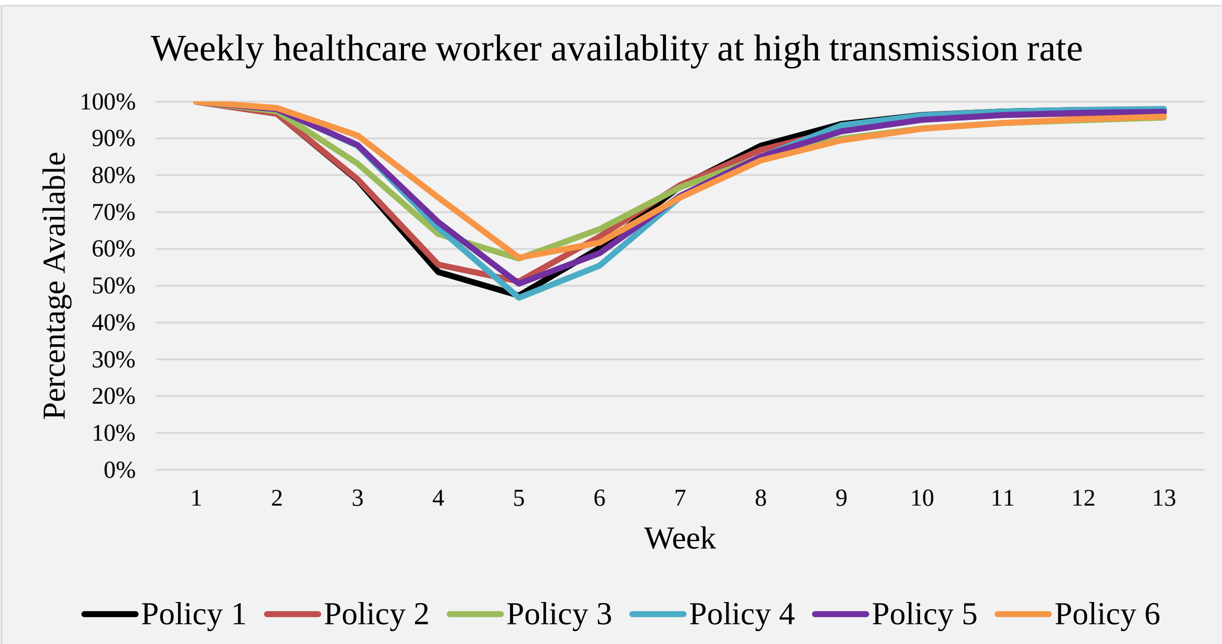

Figure 3: Average weekly healthcare worker (HCW) availability for high transmission rates.

4.2. Fifty Percent Vaccination

Here, we increase the vaccination rates to 50%, which still represents an early adoption phase of the vaccinations during the pandemic. First, we investigate the total number of HCWs infected over 90 days across various policies under each case, as seen in Table 5.

Table 5. Percentage of healthcare workers (HCWs) infected over 90 days at 50% vaccination.

Cases	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
1	47.9±1.22	46.0±0.98	40.6±0.90*†	48.2±1.01	45.8±0.71	41.0±0.88*†
2	48.0±0.34	48.1±0.55	47.9±0.81	48.5±0.15	48.3±0.11	48.0±0.56
3	49.1±0.75	49.0±0.43	48.7±0.33	49.4±0.12	48.6±0.10	48.9±0.31
4	29.0±0.33	13.3±0.45*	7.9±0.24*†	28.7±0.80	13.0±1.01*	8.1±0.94*†
5	45.9±0.54	28.5±0.62*	20.1±0.12*†	45.8±0.79	28.4±0.90*	20.2±0.56*†
6	48.7±0.32	46.8±0.74	36.7±0.85*†	48.9±0.62	47.1±0.55	36.6±0.41*†

* = significantly different from policy 1,4

† = significantly different from policy 2,5

ANOVA tests showed similar results to that of the zero vaccination scenario, where there were no statistically significant differences between the six policies (p-value > 0.05) during high patient transmission cases except for one case (Case 1). For case 1, we observed that policies 3 and 6, where HCWs are most restricted (no mixing), reported a significant reduction in the percentage of HCWs infected over the 90 days compared to policy 1 (p-value = 0.01), policy 2 (p-value = 0.02), policy 4 (p-value = 0.01), and policy 5 (p-value = 0.03).

For low patient transmission cases (4-6), we observed statistically significant differences (p-value < 0.05) in the total percentage of HCWs infected over 90 days. On performing a posthoc test, we observed that policies 3 and 6, where HCWs are most restricted (no mixing), reported a significant reduction in the percentage of HCWs infected over the 90 days compared to policy 1 (p-value < 0.01), policy 2 (p-value < 0.01), policy 4 (p-value < 0.01), and policy 5 (p-value < 0.01) across all low patient transmission cases (4-6). Additionally, we observed that the semi-restricted policy (inter-group mixing) and its rotation counterpart, i.e., policies 2 and 5, reported a significant (p-value < 0.05) reduction in the percentage of HCWs infected over 90 days compared to policy 1 and policy 4 (inter-hospital mixing) for cases 4 and 5. Similar to the zero vaccine scenario, even during low patient transmission rates when the patient census is high (case 6), inter-group mixing (policies 2 and 5) and inter-hospital mixing (policies 1 and 4) did not vary significantly. Finally, we observed that on comparing respective policies to their rotational counterparts, i.e., policy 1 vs. policy 4, policy 2 vs. policy 5, and policy 3 vs policy 6, we did not observe any statistically (p-value > 0.05) significant differences.

Next, we investigated the weekly unavailability of HCWs under each policy for different cases. Table 6 below represents the average weekly unavailability of HCWs across three low patient transmission rates at 50% vaccination rates.

Table 6. Average weekly healthcare worker (HCW) availability for low transmission rates.

Week	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	100%	100%	100%	100%	100%	100%

2	100%	100%	100%	100%	100%	100%
3	99%	99%	99%	99%	99%	99%
4	96%	97%	98%	97%	98%	98%
5	92%	96%	96%	92%	95%	96%
6	89%	94%	95%	88%	93%	94%
7	87%	94%	95%	86%	92%	94%
8	88%	94%	96%	87%	92%	95%
9	90%	94%	96%	90%	93%	95%
10	92%	95%	96%	92%	94%	96%
11	94%	95%	96%	94%	95%	96%
12	95%	96%	97%	95%	96%	96%
13	96%	96%	97%	96%	96%	97%

On investigating the peak unavailability of HCWs across the simulation period (90 days), we observed that no mixing (Policy 3) and its rotation version (Policy 6) outperformed the inter-hospital mixing and its rotation version (Policy1 and 4) by improving the peak weekly HCW availability by as much as 8%. Further, inter-group mixing (Policy 2) and its rotation version (Policy 5) outperformed inter-hospital mixing and its rotation version (Policy 1 and 4) by improving the weekly HCW availability by 7%. Figure 4 below represents the weekly availability of HCWs at a low patient transmission rate. Finally, comparing the rotation policies (Policy 4,5,6) to the respective restriction policies (Policy 1,2,3), the model predictions did not vary significantly regarding weekly provider unavailability.

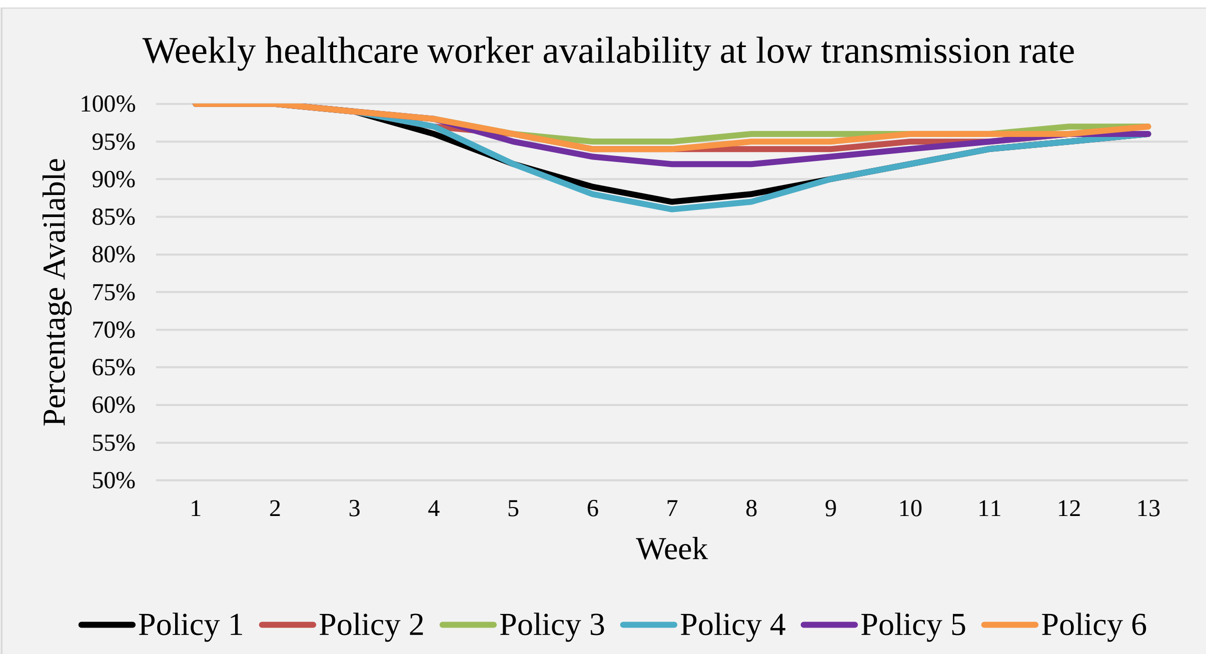

Figure 4: Average weekly healthcare worker (HCW) availability for low transmission rates.

On comparing the weekly unavailability of the HCWs under each policy during high patient transmission rates, no mixing (Policy 3) and its rotation version (Policy 6) outperformed the inter-hospital mixing and its rotation version (Policy 1 and 4) by improving the peak weekly HCW availability by as much as 7% as seen in Table 7 below. Further, inter-group mixing (Policy 2) and its rotation version (Policy 5) slightly outperformed inter-hospital mixing and its rotation version (Policy 1,4) by improving the weekly HCW availability by 4%.

Table 7. Average weekly healthcare worker (HCW) availability for high transmission rates.

Week	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	100%	100%	100%	100%	100%	100%
2	99%	99%	99%	99%	99%	99%
3	92%	93%	93%	96%	96%	96%
4	82%	85%	85%	87%	89%	89%
5	77%	81%	83%	77%	82%	84%
6	80%	83%	85%	78%	81%	83%
7	86%	87%	89%	85%	86%	87%
8	92%	91%	92%	91%	90%	91%

9	95%	94%	94%	95%	94%	94%
10	97%	96%	95%	97%	96%	95%
11	98%	97%	96%	98%	97%	96%
12	99%	97%	97%	99%	97%	97%
13	99%	98%	97%	99%	98%	97%

Although the total percentage of healthcare workers infected over the simulation length (90 days) did not vary significantly across various policies during the high patient transmission rates scenarios except for one case, as noted in Table 7 above, we observed that the no mixing policies can reduce the peak unavailability of HCWs during a specific week. While the differences in the peak HCW unavailability between the restricted policies (policies 2,3,5 and 6) compared to the most flexible policies (policy 1 and 4) are not as significant as observed during the zero-vaccination rate, they still outperform the inter-hospital mixing policies (Policy 1, 4). Figure 5 below represents the weekly availability of HCWs at a high patient transmission rate during 50% vaccination rates.

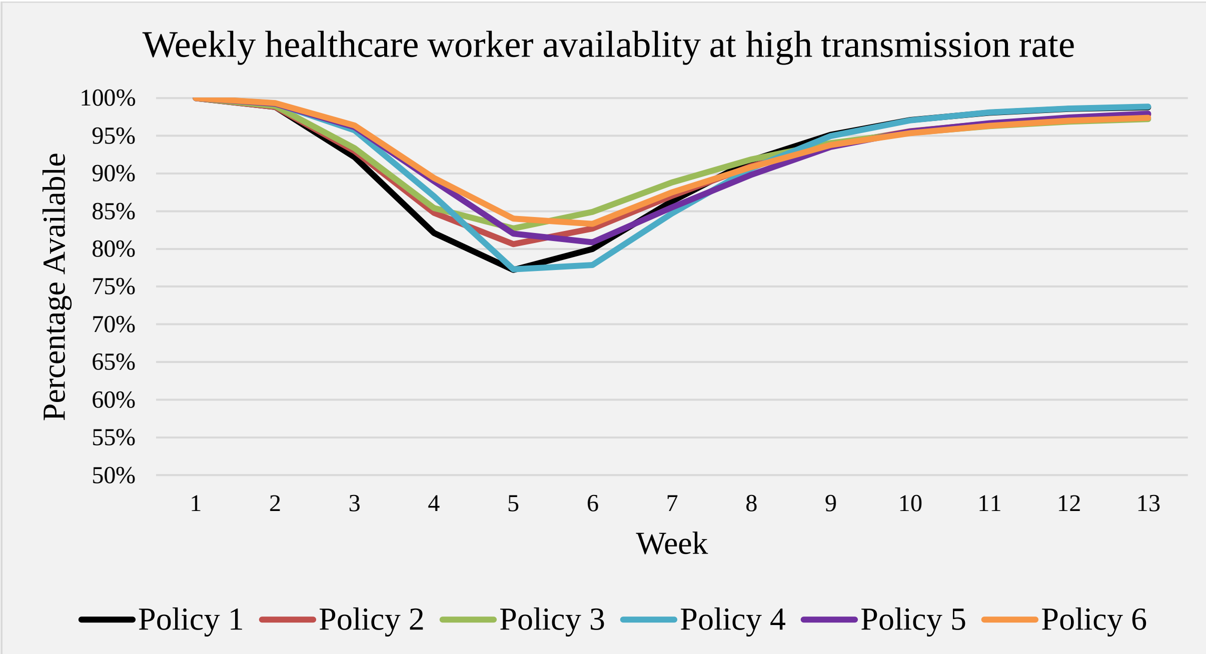

Figure 5: Average weekly healthcare worker (HCW) availability for high transmission rates.

Observations from the 0% vaccination rate and 50% vaccination rate simulations suggest that when the patient transmission rates are high, the benefits of the restrictive policies (2,3,5,6) are minimal. Moreover, we can notice that the benefits of these restrictive policies reduce when the vaccination rate increases from 0% to 50%. However, to investigate if the pattern holds, we simulate two scenarios: i) 75% vaccination rate and ii) 90% vaccination rate.

4.3. Seventy-Five Percent Vaccination

Here, we increase the vaccination rates to 75%, representing the latter stages of simulation, where most of the population is vaccinated to protect against the pandemic. Table 8 below represents the percentage of HCWs infected over 90 days across various policies under each case.

Table 8. Percentage of healthcare workers (HCWs) infected over 90 days at 75% vaccination.

Cases	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
1	23.0±0.65	21.1±0.40	19.5±0.70*	22.8±0.58	21.0±0.90	19.5±0.11*
2	24.2±0.45	23.8±0.87	24.0±0.09	24.0±0.80	23.8±0.94	23.7±0.16
3	25.5±0.33	25.0±0.61	25.1±0.33	25.0±0.23	25.1±0.77	24.4±0.29
4	8.0±0.85	6.7±0.89	4.0±0.80*	8.0±0.67	6.5±0.22	3.9±0.75*
5	19.2±1.13	13.3±0.81*	9.3±0.47*†	19.3±0.90	13.2±0.34*	9.2±0.40*†
6	24.3±0.72	22.5±1.22	16.3±0.29*†	24.3±0.73	22.8±0.32	16.3±0.87*†

* = significantly different from policy 1,4

† = significantly different from policy 2,5

ANOVA tests showed some results similar to 0 and 50% vaccination rates, where restriction policies still outperform the flexible/inter-hospital mixing policies (policies 1 and 4) for some cases. Specifically, we observed that during high-patient transmission rates, for case 1, policies 3 and 6, where HCWs are most restricted (no mixing), reported a significant reduction in the percentage of HCWs infected over the 90 days compared to policy 1 (p-value = 0.02), and policy 4 (p-value = 0.02). However, unlike what we observed during 0 and 50% vaccination rates, there were no significant differences between the inter-group and no mixing policies, again highlighting the diminished returns of restrictions as vaccination rates increase.

For low patient transmission cases (4-6), we observed statistically significant differences (p-value < 0.05) in the total percentage of HCWs infected over 90 days. On performing a posthoc test, we observed that policies 3 and 6, where HCWs are most restricted (no mixing), reported a significant reduction in the percentage of HCWs infected over the 90 days compared to policy 1 (p-value < 0.01), policy 2 (p-value < 0.01), policy 4 (p-value < 0.01), and policy 5 (p-value < 0.01) when the patient census was medium or high. However, when the patient census was low (case 4), the no mixing policies (policies 3 and 6) were only significantly better than inter-hospital mixing policies (policies 1 and 4). The no-mixing policies (policies 3 and 6) and inter-group mixing policies (policies 2 and 5) did not vary significantly.

Further, we observed that the semi-restricted policy (inter-group mixing) and its rotation counterpart, i.e., policies 2 and 5, reported a significant (p-value = 0.02) reduction in the percentage of HCWs infected over 90 days compared to policy 1 and policy 4 (inter-hospital mixing) for case 5. On comparing respective policies to their rotational counterparts, i.e., policy 1 vs. policy 4, policy 2 vs. policy 5, and policy 3 vs policy 6, we did not observe any statistically (p-value > 0.05) significant differences.

Next, we investigated the weekly unavailability of HCWs under each policy for different cases. Table 9 below represents the average weekly unavailability of HCWs across three low-patient transmission rates at 75% vaccination rates.

Table 9. Average weekly healthcare worker (HCW) availability for low transmission rates.

Week	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	100%	100%	100%	100%	100%	100%
2	100%	100%	100%	100%	100%	100%
3	100%	100%	100%	100%	100%	100%
4	99%	99%	99%	99%	99%	99%
5	98%	98%	98%	98%	97%	98%
6	97%	97%	98%	96%	97%	98%
7	96%	97%	98%	96%	96%	97%
8	96%	97%	98%	95%	96%	98%
9	96%	97%	98%	96%	97%	98%
10	96%	97%	98%	96%	97%	98%
11	97%	98%	98%	97%	97%	98%
12	97%	98%	98%	97%	98%	98%
13	98%	98%	98%	98%	98%	98%

On investigating the peak unavailability of HCWs across the simulation period (90 days) during low transmission rates, we observed that no mixing (Policy 3) and its rotation version (Policy 6) are slightly better than the inter-hospital mixing policies (Policy 1 and 4) and inter-group mixing policies (Policy 2 and 5) but not significantly better. We observed that regarding the weekly unavailability of HCWs, the restriction policies do not add any significant value when patient transmission rates are low, and the vaccination rate is over 75%. Figure 6 below represents the weekly availability of HCWs at a low patient transmission rate during 75% vaccination rates.

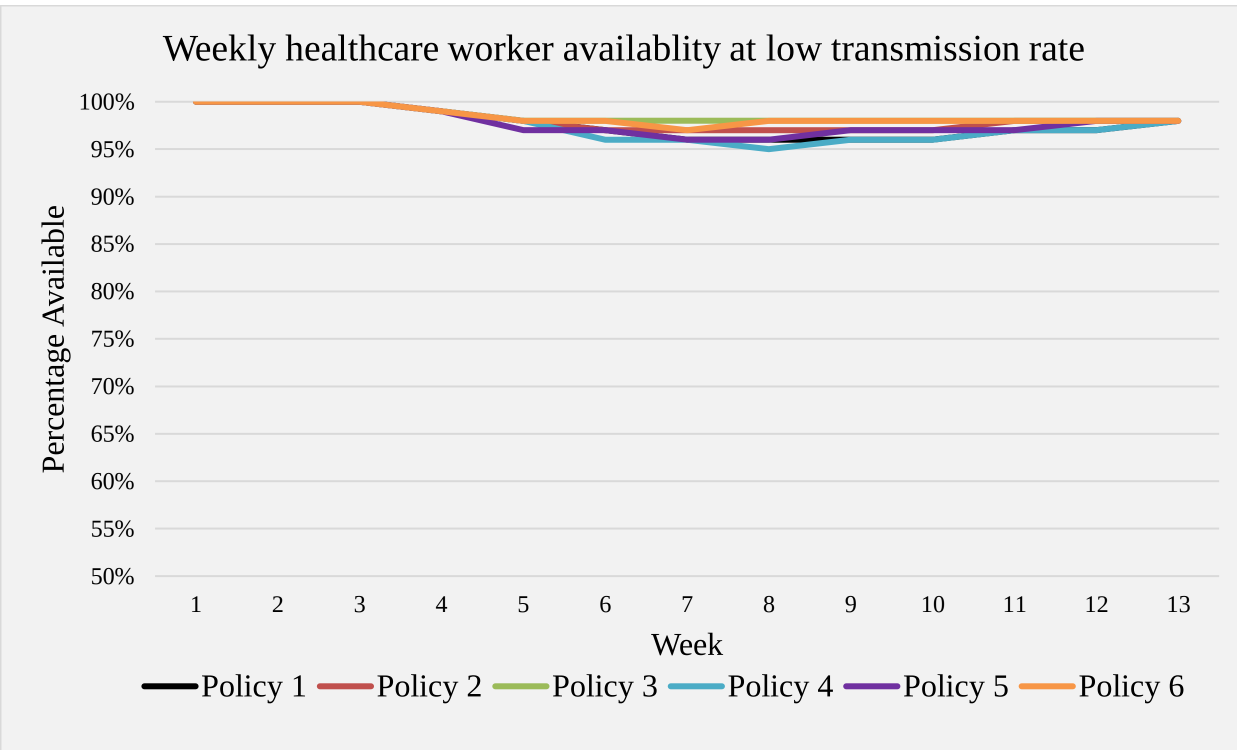

Figure 6: Average weekly healthcare worker (HCW) availability for low transmission rates.

On comparing the weekly unavailability of the HCWs under each policy during high patient transmission rates, similar to low transmission scenarios, the no mixing (Policy 3) and its rotation version (Policy 6) performed slightly better than the inter-hospital mixing policies (Policy 1 and

4) and inter-group mixing policies (Policy 2 and 5) they were not significantly better. However, it is interesting to notice that compared to the low transmission scenarios, the peak unavailability is higher during the high transmission scenarios, as seen in Table 10 below.

Table 10. Average weekly healthcare worker (HCW) availability for high transmission rates.

Week	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	100%	100%	100%	100%	100%	100%
2	99%	100%	100%	100%	100%	100%
3	97%	97%	97%	98%	98%	98%
4	93%	93%	93%	95%	95%	95%
5	90%	90%	92%	91%	91%	92%
6	91%	92%	93%	90%	91%	92%
7	93%	94%	94%	92%	93%	94%
8	95%	96%	96%	94%	95%	95%
9	96%	97%	97%	96%	97%	97%
10	97%	98%	98%	97%	98%	98%
11	98%	98%	98%	98%	98%	98%

12	99%	98%	98%	99%	98%	98%
13	99%	99%	98%	99%	99%	99%

Figure 7 below represents the weekly availability of HCWs at a high patient transmission rate during 75% vaccination rates. As mentioned above, the peak of HCW unavailability over the weeks is higher than the low transmission rates, but there is minimal benefit to the restriction policies (policies 2,3,5 and 6) compared to the current practices.

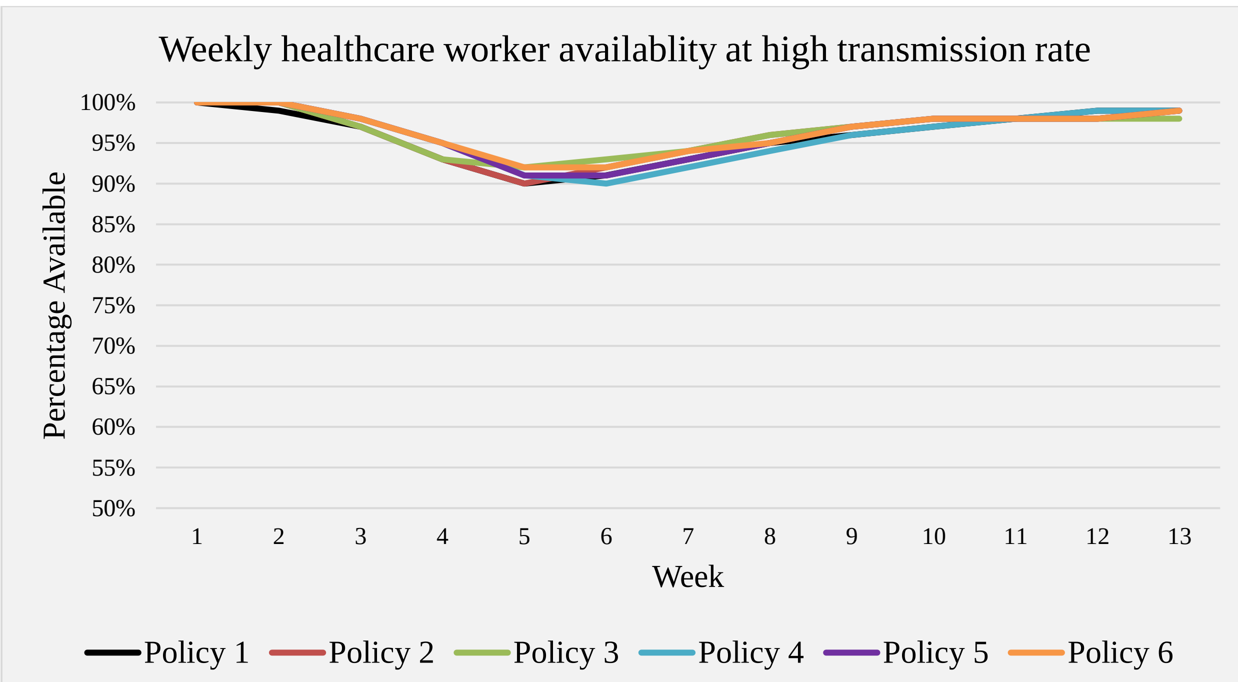

Figure 7: Average weekly healthcare worker (HCW) availability for high transmission rates.

Overall, we observed that at a 75% vaccination rate, there is only a very negligent benefit of restriction policies (policies 2,3,5, and 6) compared to the inter-hospital mixing policies (policies 1 and 4) on reducing the weekly HCW unavailability. However, we observed that no-mixing policies are still beneficial in reducing the percentage of HCWs infected over 90 days during some cases. Hence, we simulated one more scenario in which the vaccination rates were 90%.

4.4. Ninety Percent Vaccination

For this final scenario, we increase the vaccination rate to 90%, representing a recovery stage of the pandemic where almost all the population is vaccinated. While it was evident from the prior observations that the restrictive policies did not significantly reduce the weekly unavailability among HCWs at a 75% vaccination rate, there were a few cases where the restrictive policies reduced the overall HCW unavailability compared to the current practices. Table 11 below presents the percentage of HCWs infected over 90 days across various policies under each case.

Table 11. Percentage of healthcare workers (HCWs) infected over 90 days at 90% vaccination.

Cases	**Policy 1**	**Policy 2**	**Policy 3**	**Policy 4**	**Policy 5**	**Policy 6**
1	7.2±0.17	7.2±0.87	5.9±0.67	7.2±0.30	7.1±0.91	6.0±0.62
2	9.4±0.30	9.4±0.04	8.6±0.20	9.1±0.69	9.1±0.80	8.0±0.99
3	10.1±0.39	10.1±0.65	10.0±0.89	10.3±0.20	10.0±0.92	9.9±0.41
4	1.9±0.66	1.6±0.57	1.4±0.42	2.1±0.46	1.6±0.85	1.5±0.98
5	4.3±0.75	3.5±0.31	3.1±0.51	4.0±0.90	3.2±0.72	3.0±0.57

6	8.1±0.83	7.7±0.49	7.0±1.10	8.1±1.10	7.5±0.56	6.9±0.75

* = significantly different from policy 1,4

† = significantly different from policy 2,5

ANOVA tests showed that irrespective of the patient transmission rates and patient census, the restrictive policies, i.e., no mixing policies and inter-group mixing policies, did not significantly (p-value > 0.05) reduce the percentage of HCWs getting infected over 90 days compared to the current practices (inter-hospital mixing).

Although it was evident from the prior experiment that weekly HCW unavailability did not vary significantly across different patient transmission rates and patient census, we still present the findings from the simulation results at a 90% vaccination rate.

Table 12. Average weekly healthcare worker (HCW) availability for low transmission rates.

Week	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
1	100%	100%	100%	100%	100%	100%
2	100%	100%	100%	100%	100%	100%
3	100%	100%	100%	100%	100%	100%
4	100%	100%	100%	100%	100%	100%
5	99%	99%	100%	99%	99%	100%

6	99%	99%	99%	99%	99%	99%
7	99%	99%	99%	99%	99%	99%
8	99%	99%	99%	99%	99%	99%
9	99%	99%	99%	99%	99%	99%
10	99%	99%	99%	99%	99%	99%
11	99%	99%	99%	99%	99%	99%
12	99%	99%	99%	99%	99%	99%
13	99%	99%	99%	99%	99%	99%

Figure 8 below represents the weekly availability of HCWs at a low patient transmission rate during 90% vaccination rates.

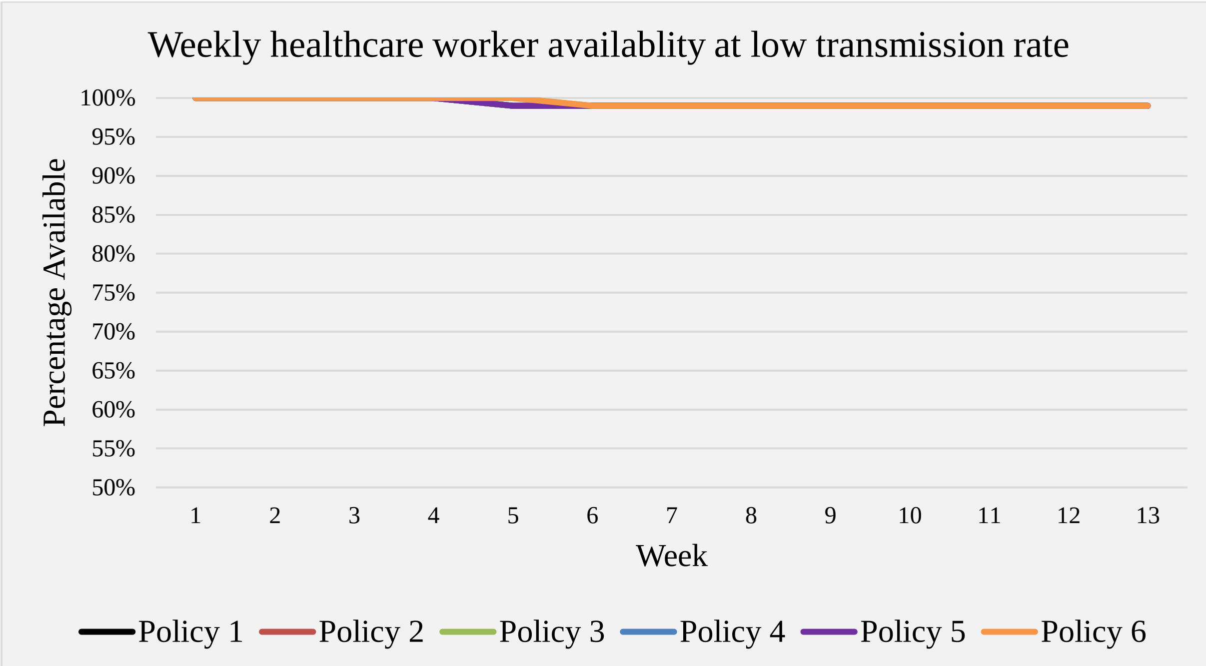

Figure 8: Average weekly healthcare worker (HCW) availability for low transmission rates.

While the peak unavailability was slightly higher at higher patient transmission rates compared to the low patient transmission rate, the overall availability was always 95%. Table 13 below represents the weekly availability at a 90% vaccination rate at a high patient transmission rate.

Table 13. Average weekly healthcare worker (HCW) availability for high transmission rates.

Week	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
1	100%	100%	100%	100%	100%	100%
2	100%	100%	100%	100%	100%	100%
3	99%	99%	99%	99%	99%	99%

4	97%	98%	98%	98%	98%	99%
5	97%	97%	98%	97%	97%	98%
6	97%	97%	98%	97%	97%	98%
7	98%	98%	98%	97%	97%	98%
8	98%	98%	98%	98%	98%	98%
9	99%	99%	99%	99%	98%	99%
10	99%	99%	99%	99%	99%	99%
11	99%	99%	99%	99%	99%	99%
12	99%	99%	99%	99%	99%	99%
13	99%	99%	99%	99%	99%	99%

Figure 9 below represents the weekly availability of HCWs at a high patient transmission rate during 90% vaccination rates.

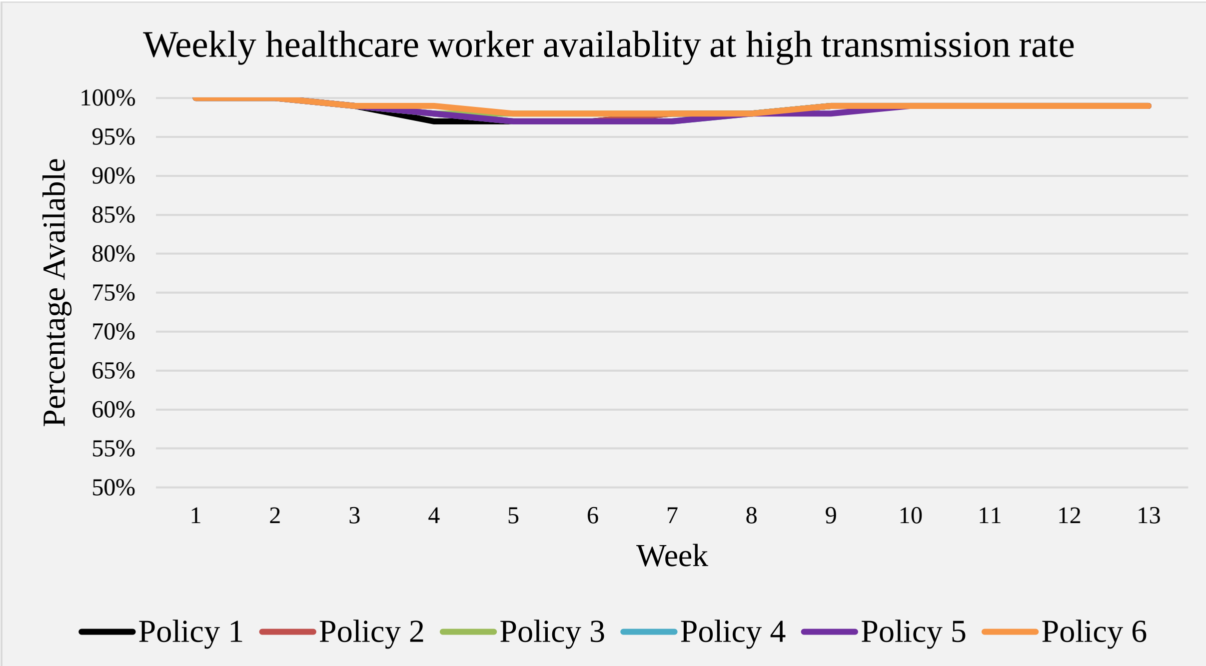

Figure 9: Average weekly healthcare worker (HCW) availability for high transmission rates.

The simulated findings indicate that at a 90% vaccination rate, irrespective of patient transmission rate and patient census, restrictive staffing policies have no statistically significant impact in reducing the weekly HCW unavailability and overall percentage of HCWs getting infected over 90 days.

CHAPTER 5: DISCUSSIONS & CONCLUSIONS

Protecting HCWs during a pandemic is critical for delivering timely and quality care to increased patient demands often reported during public health crises. Additionally, HCWs are on the front lines of combating the outbreak, risking their lives daily to provide care; hence, their safety not only preserves their well-being but also maintains the integrity of the healthcare system, as their expertise and dedication are indispensable assets in managing the crisis effectively. Furthermore, safeguarding HCWs is essential for maintaining public trust and confidence in the healthcare system. If healthcare professionals are not adequately protected, it can lead to increased transmission of the virus within healthcare settings, exacerbating the strain on resources and potentially leading to higher mortality rates. Moreover, protecting healthcare workers is a moral imperative, as they have taken an oath to care for the sick and vulnerable. Failing to prioritize their safety jeopardizes their health and undermines the fundamental principles of compassion and solidarity upon which healthcare is built. In essence, safeguarding HCWs is a practical necessity and reflects our societal values and collective responsibility to protect those who selflessly serve others in times of crisis.

This research investigated the impact of different restriction policies, such as segregating and rotating HCWs, on reducing their peak weekly unavailability of HCWs and unavailability over three months during various stages of the COVID-19 pandemic at a large health system with multiple locations. Specifically, this study furthers the research by incorporating various pandemic parameters such as patient census, HCW types, transmission rates, vaccination rates, interactions, reinfection, and other COVID-19 data along with multiple hospital locations which no prior studies have considered while investigating staffing policies among perioperative HCWs (Habib & Zinn,

2020) (Mascha et al., 2020) (Kluger et al., 2020). By simulating 24 scenarios for 90 days by changing the patient census, transmission rates, and vaccination rates at multiple hospital locations, our findings indicate that segregating and rotating the HCWs could significantly reduce the peak weekly HCW unavailability and percentage of HCWs getting infected over the simulation period. Specifically, observations from simulated scenarios suggest that segregating HCWs into smaller groups within a facility (no mixing), restricting them to a single facility (inter-group mixing), and rotating (alternating the HCWs) shift can significantly reduce the COVID-19 exposure and infection spread, thereby reducing HCW shortage during specific scenarios.

Although findings regarding the rotation schedules align well with prior single-site studies, they did not consider the impact of changing patient census, vaccination, and transmission rates. This research shows the importance of modeling these parameters (patient transmission rates, patient census, vaccination rates, etc.) as we observed that the benefits of the rotation policies diminish as the vaccination rates increase or have no significant benefit when transmission rates are higher. Furthermore, this work provides the empirical performances of two restriction policies (segregation within a facility and restriction to a single facility) through simulations that no other prior studies have considered. Furthermore, these restriction policies integrated with the rotation schedules performed better than the current practices during specific scenarios, which other studies have not considered. These observations are critical for other health systems with multiple locations to consider in order to improve HCW availability.

Although our research focused on modeling the perioperative staff (anesthesiologists, nurse anesthetists, and nurses), the observations from this study can be considered while developing staffing schedules for other high-risk HCW populations such as emergency medicine, hospitalists, etc., to reduce the HCW unavailability. Additionally, while the current observations are based on the data from the COVID-19 pandemic, the model can be used to simulate other pandemic or infectious diseases where the SEIR compartmental model is still relevant. Moreover, the model is coded and developed in a format that allows for generalization where health systems with multiple locations can change the model parameters (beds, HCWs types, etc.) and thereby help better prepare and assign their HCW workforce during future pandemics.

As briefly mentioned above, we observed that segregating HCWs into smaller groups within a facility (no mixing), restricting them to a single facility (inter-group mixing), and rotating (alternating the HCWs) shift can significantly reduce HCW unavailability during low vaccination rates and low patient transmission rates. Specifically, when vaccination rates were 50% or less, we observed that segregation policies (no mixing and inter-group mixing) and their rotation versions reduced the weekly unavailability of HCWs by as much as 40% compared to the current practices at the partner health system. Moreover, the total number of HCWs getting infected over the 90 days was reduced by as much as 60%, thereby significantly improving HCWs' availability to provide care. However, when the vaccination level increases to 75%, the segregation policies (no mixing and inter-group mixing) and their rotation versions are not significantly better in reducing the peak weekly unavailability of the HCW. Still, these policies were beneficial in reducing the total number of HCWs infected over the three months. Finally, when the vaccination levels increased to 90%, segregation policies, and rotation versions did not significantly reduce the peak HCW unavailability or the percentage of HCWs getting infected over 90 days. These observations further highlight the importance of incorporating factors such as vaccination rates, patient transmission rates, and patient census while modeling similar infectious diseases in health systems.

Although this research study aimed to comprehensively model an SEIR compartmental model with an ABM-based computational model to simulate a pandemic scenario for HCW staff scheduling, which can be generalizable to multi-location health systems, this study has a few limitations. First, the analysis and results are based on simulated findings as opposed to applied results. However, our simulated results are reported with a 99% confidence interval. Another limitation is that we assume that each patient, on average, comes in contact with a provider a certain number of times, and providers interact with each other at a particular rate. Although these assumptions are based on expert opinions from anesthesiologists working in the partner hospital, we recognize the fact that the number of actual interactions could be higher in the OR when the HCWs could be in close contact most of the time and lower while providing care on inpatient beds, depending on the scenario. However, to reduce the complexity of modeling these different workflows, we decided to use the average, as we aimed to compare various staffing policies (flexible vs. restricted) during various stages of a pandemic (early, medium, and late) without changing any workflow/processes. In the future, the model could be updated to incorporate a detailed workflow.

Another limitation is associated with modeling and replicating the partner hospital's activities. While physicians were involved throughout the model development process to replicate the actions, we acknowledge that certain assumptions (interactions) and simplifications of complex workflow in the model could limit the ability to replicate the activities at the partner hospital completely. Additionally, the time until provider availability after infection is based on the recovery time and isolation guidelines from the CDC, but we recognize that some hospitals may have different practices, and these durations might vary. Finally, from a modeling standpoint, future research should consider dynamic policies that switch between different policies discussed in the research during the 90-day period rather than keeping the model static over the simulation duration. Doing this would allow hospitals to dynamically adapt their policies to protect HCWs during a surge in a pandemic or to account for quick changes observed during a pandemic.

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