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INVESTIGATING THE IMPACT OF PANDEMIC ON THE PERIOPERATIVE HEALTHCARE WORKERS AVAILABILITY: AN AGENT-BASED APPROACH

Shweta Prasad[1], Vishnunarayan Girishan Prabhu[2], William Hand[3]

[1]Industrial and Systems Engineering Department, University of North Carolina at Charlotte, NC, USA
[2]School of Modeling Simulation Training, University of Central Florida, Orlando, FL, USA
[3]Department of Anesthesiology, PRISMA Health - Upstate, Greenville, SC, USA

ABSTRACT

Protecting healthcare workers (HCWs) during a pandemic is critical to provide timely medical care for patients. Although prior studies have investigated HCW unavailability during the COVID-19 pandemic, the studies have not investigated the impact of parameters such as patient census, vaccination rates, transmission rates, and multiple hospital locations on HCW availability. This research considers a high-risk HCW group of perioperative staff to investigate the impact of segregating and rotating staffing policies on HCW unavailability during a pandemic in a health system with multiple locations. An agent-based model with a SEIR compartmental model was developed to simulate various scenarios. Simulated findings indicate that segregating and rotating policies significantly (p-value <0.01) reduced the peak weekly unavailability of HCWs and the total percentage of HCWs getting infected by as much as 25% and 60% when vaccination rates were lower (<75%). However, these benefits diminished when the vaccination rates increased to 75%.

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 (Ali & Alharbi, 2020). The economic fallout has resulted in job losses, business closures, and financial insecurity for countless individuals and families (Ali & Alharbi, 2020). Additionally, lockdowns, travel restrictions, and social distancing measures have altered daily routines and social interactions, contributing to widespread mental health challenges. According to the World Health Organization (WHO), approximately 775 million COVID-19 cases were recorded, and 7 million deaths were associated with the COVID-19 pandemic as of 2024, reinforcing the magnitude of the crisis (World Health Organization, 2024).

While the impact of COVID-19 was profound across various industries, healthcare systems have been strained to their limits (Haldane et al., 2021). Health systems face 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 (Haldane et al., 2021). 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 HCWs. 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.

Contact with infected surfaces and droplets/aerosol are the two main ways that COVID-19 is spread from person to person. Studies investigating the transmission of SARS-CoV-2 from patients to HCWs have reported that specific procedures such as suctioning, bronchoscopy, intubation, or cardiopulmonary resuscitation pose a higher risk of infection spread from patients to HCWs. The perioperative team is considered a high-risk group for COVID-19 exposure as they come in close contact with a patient's airway and aerosols generated during certain medical procedures where the SARS-CoV-2 virus remains infectious for hours (Kharasch & Jiang, 2020; Mazzola & Grous, 2020; van Doremalen et al., 2020; Zhang et al., 2020). Staffing shortages and unavailability among perioperative teams lead to delayed patient care and poorer healthcare outcomes, including reduced quality-adjusted life years, disease-free survival, and, in the worst-case scenario, surgery cancellations, which also negatively affect the hospital finances (Fu et al., 2020; Karimuddin et al., 2021; Whittaker et al., 2021).

Given the critical nature of protecting the HCW during a pandemic such as the one brought on by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), researchers have investigated various staffing policies over the last two years. Among these, we identified three simulation-based studies among the perioperative population, where the first study reported that longer shifts and avoiding staggering rotations of HCW shifts could reduce infection among HCWs (Kluger et al., 2020). The second study observed that the longer shifts with continuous breaks significantly reduced HCW shortage, and the effect progressively increased as the probability of infection increased (Mascha et al., 2020). Finally, another study that implemented a staffing policy where neurosurgery residents were divided into two teams and alternated weekly with minimal contact observed that the teaming approach minimized the risk of exposure and provided the needed rest for residents (Habib & Zinn, 2020).

Although prior studies have investigated and reported the effectiveness of various strategies in reducing HCWs' infection and unavailability, these have been restricted to a single or small facility and do not account for how individual system factors interact with each other and impact the infection spread. Moreover, from a modeling standpoint, none of these studies have integrated advanced computational models, such as Agent-Based Models (ABMs), with compartmental models, including Susceptible (S), Exposed (E), Infectious (I), and Recovered (R) (SEIR), for addressing HCW unavailability. The use of agent-based modeling (ABM) has gained popularity in healthcare operations management literature and, particularly, in the infectious disease prevention and control domain (Barnes et al., 2013). Capable of modeling and simulating the actions of various autonomous individuals including physicians, nurses, and patients, jointly with the interactions among them, ABM-based approaches have provided additional insights with more realistic models for disease spread and assessment of various health service operations (Tracy et al., 2018); (Chumachenko et al., 2018; Crooks & Hailegiorgis, 2014; Khalil et al., 2012; Perez & Dragicevic, 2009).

Researchers have used ABM-based simulations in the infectious disease literature over the last several years. Utilizing an ABM approach (Barnes et al., 2010) investigated the performance of various infection control measures, such as hand hygiene, patient screening, and patient isolation, to control the transmission of Methicillin-resistant Staphylococcus aureus (MRSA) spread within a hospital. They showed that increasing hand hygiene compliance is more effective than hiring additional healthcare workers to minimize MRSA transmission, and hand-hygiene compliance must still be supplemented with other measures to effectively prevent transmission. In another study, researchers used ABM simulation to model an outbreak scenario to capture the nonhomogeneous transmission and infection rates where the model serves as a decision support tool, predicting disease spread during a pandemic, generating a map of the estimated disease spread area within the geography of interests, and assessing the relative effectiveness of various mitigation strategies to control the disease (Aleman et al., 2011). Studies have also used ABM to evaluate the effectiveness of medication administration, hand hygiene, isolation, and disinfection with bleach to identify their impact on the natural progression of Clostridium Difficile in patients and its transmission in a midsized hospital among patients, HCWs, and visitors (Codella et al., 2015). Several studies have also used the SEIR compartmental model to understand the dynamics of disease transmission, allowing researchers to simulate and predict the spread of infectious diseases (He et al., 2020; Stehlé et al., 2011).

While researchers have used ABM and SEIR models to capture infection spread, they have not integrated ABM with the SEIR compartmental model to investigate the infection spread among HCWs in a multi-hospital health system. By including factors such as vaccination rate among HCWs, infection transmission rates, the number of patient-HCW and HCW-HCW interactions by different HCW types, and patient census in the hospital, we developed an ABM simulation that uses an SEIR compartmental model.

This approach allowed us to gather in-depth insights into disease spread and identify the best staffing policy that minimizes infection spread and unavailability among the perioperative team at Prisma Health.

2 METHODS

2.1 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 it should be noted that the Patient-HCW contact rate is impacted by the HCW type as the number of interactions are different based on HCW type.

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. Additionally, it should be noted that we consider a higher provider transmission rate because in non-care providing places such as recovery room, workstations, etc., the HCWs tend to be less cautions and don't mask themselves or wear gloves.

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 (Centers for Disease Control and Prevention, 2021). The possibility of reinfection was considered for HCWs returning to work after the mandatory quarantine since multiple studies reported such cases (Bergwerk et al., 2021; Centers for Disease Control and Prevention, 2022). 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 (0.004% and 0.04%). 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[2]	4.0%
Patient transmission rate[1]	0.04% or 0.004%
Incubation period[1]	Triangular (2,4,12) days
Asymptomatic probability[1]	40%
Quarantine period[2]	5/10/14 based on vaccination
Mortality rate[1]	1.8%
Reinfection Rate[1]	0.0004%
Immunity period[1]	60 days
Transmission rate after vaccination[1]	12.5% of transmission rate
Providers and Patients vaccinated[2]	0% or 50% OR 75% or 90%
Workforce testing frequency[3]	1 per week
Patient Census[3]	700-108-34 based on location
Number of interactions between providers per hour[2] • Anesthesiologists and Anesthesiologists • Anesthesiologists and Nurse Anesthetists/Nurses • Nurse Anesthetists and Nurses	 3 per hour 1 per hour 3 per hour
Number of interactions between providers and patient[2] • Anesthesiologists and patients • Nurse Anesthetists/Nurses and patients	 2 per patient 3 per patient

1=Literature, 2=Assumption based on expert opinion, 3=Operational data from hospital

2.2 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 as a result of the infection (see Table 1), 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.

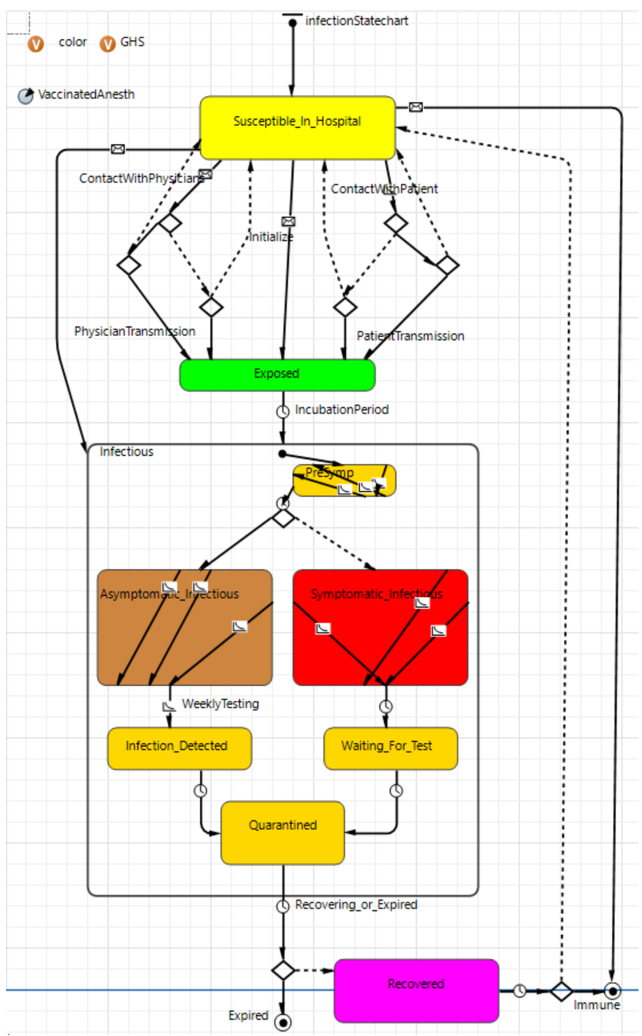

Figure 1: HCW state chart.

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.

2.3 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. In our simulation, 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 were run for a simulation horizon of 90 days 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 +/- 0.1. A one-way ANOVA was utilized to compare if the total percentage 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. For both statistical tests, an $\alpha = 0.05$ was used.

3 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, 27.5% nurse anesthetists, and 8.2% anesthesiologists.

3.1 Zero Percent (0%) and 50% Vaccination

These two policies correspond to the early phase of the pandemic when no vaccines are available and an early adoption where vaccine availability is limited. 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 0% and 50% vaccination.

Vaccination Rate	Cases	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
0%	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*†
50%	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

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) across two vaccination rates. 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 90 days compared to policy 1 (p-value < 0.05).

For low patient transmission cases (4-6) across two vaccination rates, 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 for each policy for different cases at two vaccination rates and two patient transmission rates. At 0% vaccination, across low and high patient transmission rates, we observed that the no mixing policies (Policy 3 and 6) outperformed other policies (Policy 1,2,4,5) by improving the weekly HCW availability by as much as 22% and 11%. Furthermore, inter-group mixing policies (Policies 2 and 5) outperformed inter-hospital mixing and its rotation version (Policies 1,4) by improving the weekly HCW availability by 13% and 4%. At 50% vaccination across low and high patient transmission rates, we observed that the no mixing policies (Policy 3 and 6) outperformed other policies by improving the weekly HCW availability by as much as 8% and 7%. Furthermore, inter-group mixing policies (Policy 2 and 5) outperformed inter-hospital mixing and its rotation version (Policy 1,4) by improving the weekly HCW availability by 7% and 4%. Finally, we observed no significant difference between the rotation policies (Policy 4,5,6) and the respective policies (Policy 1,2,3). Figure 2 below represents the weekly availability of HCWs at a low patient transmission rate at 0% percent vaccination rate.

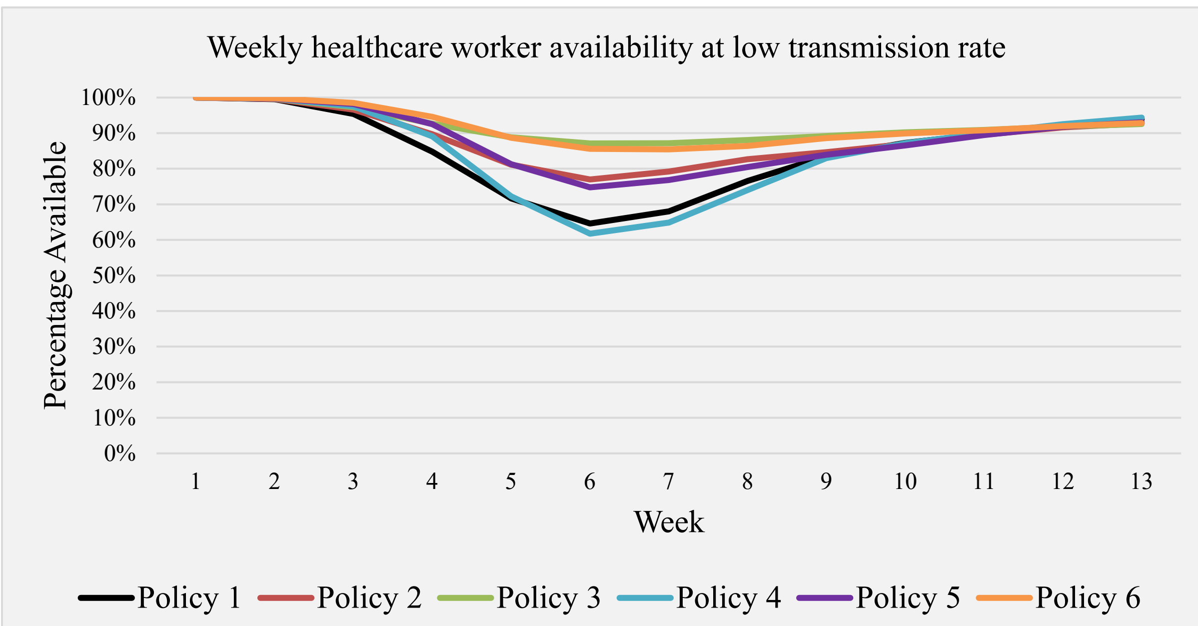

Figure 2: Average weekly healthcare worker (HCW) availability for low transmission rates 0% vaccination rate.

3.2 Seventy Five Percent (75%) Vaccination and 90% vaccination

Next, we present results from 75% and 90% vaccination rates, representing the latter stages of the pandemic, where most of the population is vaccinated to protect against the pandemic. Table 3 below represents the percentage of HCWs infected over 90 days across various policies under each case.

Table 3: Percentage of healthcare workers (HCWs) infected over 90 days at 75% and 90% vaccination.

Vaccination Rate	Cases	Policy 1	Policy 2	Policy 3	Policy 4	Policy 5	Policy 6
75%	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*†
90%	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

For the 75% vaccination rate, 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.

For 90% vaccination rate, 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).

Next, we investigated the weekly unavailability of HCWs for each policy for different cases at two vaccination rates and two patient transmission rates. For both vaccination rates under both patient transmission rates, we observed that the no mixing policies (Policy 3 and 6) performed slightly better than the inter-hospital mixing policies (Policy 1 and 4) and inter-group mixing policies (Policy 2 and 5) in improving the weekly availability of HCWs but they were not statistically significant. However, it was interesting to notice that the peak HCW unavailability was higher during the high transmission scenarios than the low transmission scenarios. Furthermore, we observed that the peak HCW unavailability was higher when only 75% of HCWs were vaccinated compared to 90% vaccination.

4 CONCLUSIONS AND FUTURE WORK

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 is indispensable in managing the crisis. Furthermore, 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.

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; Kluger et al., 2020; Mascha 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, 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 to understand their impact on HCW availability.

While 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 HCWs during future pandemics.

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.

Further, from an operational and implementation standpoint, there are two primary limitations. First, we only consider infection-related unavailability. However, there are additional factors, such as higher levels of burnout and attrition during a pandemic such as COVID-19, which could worsen the unavailability of HCWs. Second, we do not consider the preference of HCWs in this study. For example, most providers might prefer Policy 1, which allows for the most flexibility. Hence, implementing no-mixing policies or restrictive policies could lead to additional unavailability through HCW attrition.

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. 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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AUTHOR BIOGRAPHIES

SHWETA PRASAD is a graduate student in the Industrial and Systems Engineering at the University of North Carolina at Charlotte. Her research interests includes simulation modeling in healthcare. Her email address is sprasad7@charlotte.edu.

VISHNUNARAYAN GIRISHAN PRABHU is an Assistant Professor in the School of Modeling Simulation Training at the University of Central Florida. His research interests include developing mathematical models, simulation models and machine learning models to improve healthcare. His email address is vishnunarayan.girishanprabhu@ucf.edu.

WILLIAM HAND is the Vice Chairman of Academics in the Department of Anesthesiology and Perioperative Medicine at Prisma Health and an Assistant Professor at the University Of South Carolina Greenville School of Medicine. He specializes in studying the application of dynamic physiologic parameters, simulation-based perioperative crisis management, and liver transplant anesthesia. His email address is William.Hand@prismahealth.org.