Capacity Assessment and Planning of COVID-19 Vaccination Sites: A Mathematical and Simulation Approach.

by

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Thesis submitted in partial fulfillment of
the requirements for the degree of
Master of Science in Global Health
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<u>ABSTRACT</u>

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Abstract

Background: To control and minimize the spread of COVID-19, vaccination among the population to achieve herd immunity is important. However, optimizing the vaccination capacity for facility-based vaccination sites and mass vaccination sites is challenging. Additionally, evaluating the impacts of different patient flow arrangements for mass vaccination sites is hard in practice. A study to answer those questions is needed to improve the operation of COVID-19 vaccination sites and reduce the waiting time for patients and cost.

Methods: Initially, the time-motion method was used to evaluate the real-world health facilities' COVID-19 vaccination capacity in China. Then, optimization models were built to determine the optimal capacity levels for different vaccination sites based on the time-motion data. Furthermore, the impacts of different patient flow arrangements were investigated in mass vaccination sites through a discrete event simulation approach.

Results: The optimization models established in this study provide tools for policymakers to optimize the capacity level of walk-in COVID-19 vaccination sites for different vaccination targets while considering the cross-infectious risk. Compared to facility-based vaccination sites, a single mass vaccination site will require fewer service desks than using multiple facility-based vaccination sites. The mass vaccination site arranged with an optimal capacity level using a pooled queue tends to be more flexible compared to real-world arrangements.

Conclusions: This research developed a modeling framework that can help to optimize the service capacity level, identify the trade-off points for vaccination planning, and reduce the cost of operating the vaccination sites to aid in the planning of the COVID-19 vaccination site.

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Acknowledgements

First, I would like to express my sincere gratitude to my advisors Dr. Shenglan Tang and Dr. Can Zhang. It was my great honor for me to be advised by Dr. Tang and Dr. Zhang at Duke. Many thanks to Dr. Tang for leading me into the field of health service research and to Dr. Zhang's guidance for applying tools from operation management and decision sciences in the public health area. Words cannot express how grateful I am for their assistance with my studies and career. I would also like to thank my thesis committee member, Professor Wendy Prudhomme-O'Meara from Duke University, who provided invaluable comments to my thesis for improvement.

Many thanks to professors and colleagues who helped in this research. I sincerely appreciate Professor Xiaolin Xu, Ms. Danyang Wang, Mr. Duanhui Li from Zhejiang University, Professor Shuyun Xie from Zhejiang CDC, and Ms. Weixi Jiang from Duke Kunshan University for their assistance in data collection. I would also thank Mr. Lei Guo from Duke University for his help to improve my thesis.

Furthermore, I would especially like to thank Dr. Weiming Tang from the School of Medicine, the University of North Carolina at Chapel Hill (UNC), who led me to the public health field patiently and offered me research opportunities to enrich my research experience. He always gives me continuous support and help. Also, I would like to thank the wonderful UNC-Project China (SESH) team, it is really an honor and pleasure to work with them.

I would also like to thank my friends who support me during my graduate study.

Last but not the least, I would to express my greatest gratitude to my dear family members, who provide endless love and support for me.

1. Introduction

1.1 Overview of COVID-19 vaccination sites

COVID-19 has developed into a pandemic on a global scale. There have been about 300 million infections and nearly 5.5 million deaths worldwide as of February 4th, 2022 [1]. Developing herd immunity is critical for pandemic control. When a large proportion of the population develops immunity to the virus, it will be able to control its spread [2]. Vaccination is one of the safest methods for establishing herd immunity in the community [3, 4].

To operate those vaccination sites successfully, it is necessary to ensure the entire process is safe, efficient, and effective. Considering the high transmission rate of COVID-19, reducing the waiting time for people at the vaccination site is also important to decrease the cross-infection risk [5]. Meanwhile, the vaccination site also needs to have adequate vaccination capacity. Most nations now operate two kinds of vaccination sites [6]. The first is the facility-based vaccination site which we define as using existing healthcare institutions (like hospitals, clinics, community healthcare centers, and township health centers) as routine vaccination sites. This allows existing healthcare facilities to provide vaccination services to the surrounding population to facilitate uptake. However, it is impossible to vaccinate many people in a short time regardless of how close some of these facilities are to the communities they serve [7]. The second is mass vaccination sites which refer to public areas with large spaces (like stadiums, town squares, and schools) temporarily converted into vaccination sites to complement standard facility-based vaccination sites [8, 9]. This type of setting can vaccinate lots of people in a short period but require a lot of undisrupted financial, human, and medical resources for successful implementation.

1.2 Tools in operations research applied in health service research

Currently, determining the optimal capacity levels and the effects of different patient flow arrangements on various types of vaccination sites is challenging. Researchers often resolved these concerns using tools from operations research, such as the time-motion method, simulation modeling, and optimization methods [10, 11].

The time-motion method is a helpful way to evaluate a medical system's efficiency and workflow-related factors. This process enables a quantitative assessment of service capacity by utilizing external observers to collect critical information regarding the duration and movement required to complete a specific task, followed by additional analysis to identify inefficient components of the overall system and improve them [12]. This method has been widely adopted in evaluating and improving vaccination service capacity and applied in a recent study investigating the relationship between vaccine dose, different vaccines, and vaccine administration for cost and efficiency [13-17].

The simulation approach, especially the discrete event simulation model, is another method that can evaluate the performance of a health service using simulated modeling. The simulation approach is a computer-based modeling method predominantly used for comparing operation designs and predicting consequences [18]. These prediction characteristics enable researchers and policymakers to answer the "what if" question by varying the operational scenarios to determine the optimal operational designs based on the predicted outcomes. This eliminates the need for real-life "try and error" attempts in healthcare facilities, which may be costly, time-consuming, and less practical to evaluate by a real-world observational study [10, 19].

Additionally, researchers always used optimization methods to find solutions to improve the health service capacity [20]. Typically, an optimization model consists of three components: objective, decision variables, and constraints. Based on these components, the model can determine the optimal value of decision variables under different conditions to reach a predetermined target (like minimizing the cost for operating a vaccination site) [21]. These optimization methods have been widely used to determine the optimal service capacity levels for community health facilities [22], long term care [23], and outpatient clinics [24] recently.

With those tools from the operation research area, public health researchers can improve health service systems more efficiently, provide references for policymakers to make decisions, and increase access to healthcare services for the general population.

1.3 Research purpose

Currently, few studies integrate the time-motion method, simulation model, and optimization programming to evaluate and optimize COVID-19 vaccination operational design. Although several studies have developed simulation models for assessing the effectiveness of mass vaccination sites and facility-based vaccination sites operational design [25], optimal planning is absent for COVID-19 vaccination capacity under different vaccination targets [26]. To avoid unnecessary costs and improve operational performance, it is necessary to optimize the planning for the vaccination site in advance. Hence, this study aimed to optimize the operational design for COVID-19 vaccination sites during the pandemic by developing a modeling framework. The specific research aims were as followed:

Research aim 1: Collect real-world data from vaccination sites to facilitate the building of a model framework.

Research aim 2: Develop a modeling framework for optimizing the capacity level of facility-based vaccination sites and mass vaccination sites to minimize the cost under different targets.

Research aim 3: Compare the operation performance of different patient flow arrangements in mass vaccination sites.

2. Methods

2.1 Study design

This study consists of a time-motion study, optimization modeling, and simulation modeling. First, a time-motion study was conducted to assess health facilities' vaccination capacity in Zhejiang Province, China. In the second stage, optimization models were developed using the time-motion data to determine the optimal capacity planning for facility-based and mass vaccination sites. In the final stage, we integrated the simulation model into the modeling framework to investigate the impact of different patient flow arrangements and capacity levels on mass vaccination operations.

2.2 Study settings

From October to November 2020, we conducted a time-motion study in two cities (X and Y) in Zhejiang Province, China. We selected two counties in each city and coded them as X1, X2, Y1, and Y2 in this article for confidentiality concerns. The selection of the four counties was based on their shared use of the same vaccination information system, which made data collection more convenient. We also selected 6 health facilities across the four counties based on findings from a feasibility assessment conducted by our local collaborators.

2.3 Data collection

The time-motion data was collected by investigators from Zhejiang University, the Zhejiang Center for Disease Control and Prevention, Duke University, and Duke Kunshan University. Trained investigators equipped with tablets collected the time-motion data at each session of the vaccination process. Each health facility assigned 6-7 investigators based on the number of service desks at each session and the research team's human resources. These field investigators received detailed training on using the time-recording application on the tablet and how to complete the spreadsheet to collect information before the pilot study. The pilot study mainly tested the feasibility of the application, the familiarity of investigators with the application, and the degree of disruption of this research to their routine vaccination tasks.

The investigators observed the registration and vaccination sessions to map out the procedures and number of steps involved in each session. The registration session procedures included entering the relevant identification information of the vaccinated person and registering the number. The vaccination session included the opening of the vaccine package and the whole process of giving the vaccine to the people who were getting it. The tablets had a time recording application that enabled investigators to record the overall time spent by each patient on each sub-task during the registration and vaccination process. Individual accounts were created on the app to record the time spent on each sub-task separately (see Figure 1). During rush hours (periods when many people arrived together), all investigators at each vaccination site observed continuously for one hour, followed by a 15-minute break, and then continuously for another one hour. The survey session ended earlier when the peak period was shorter than two hours.

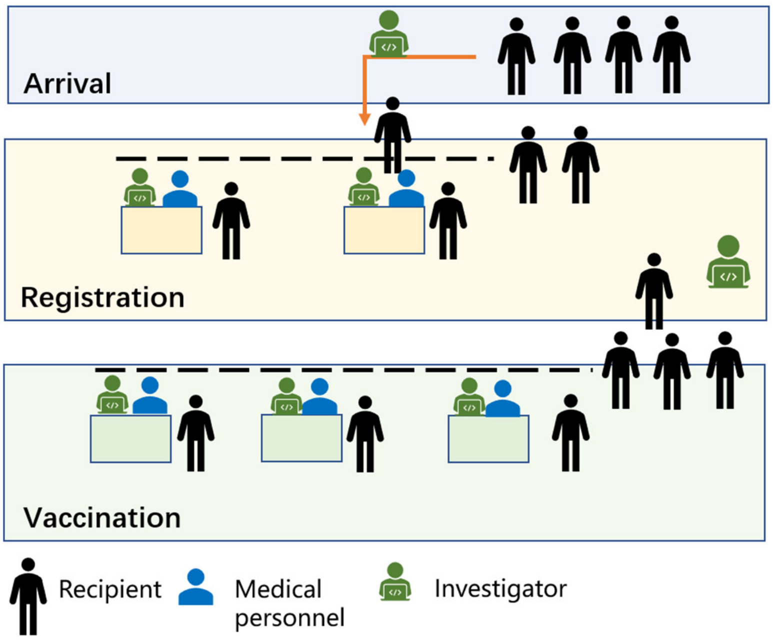


Figure 1. The conceptual diagram of the time-motion study. *

**This figure showed how the data be collected in the time-motion study. The study area consisted of arrival, registration, and vaccination. Each service desks had an investigator to record the time.*

The specific procedure of the observation was as followed: for the registration site, an investigator continuously recorded the time of each recipient from the time each recipient walked to the service desk to start registration to the time he/she left the service desk to go to the vaccination site; for the vaccination site, an investigator continuously recorded the time each person walked to the vaccination site and the time he/she left that room. The number of COVID-19 vaccinations given was recorded. The variable cost of the vaccination process in each step was collected as well, which included the cost of nurse per hour, the cost of healthcare personnel per hour, and the cost of vaccination consumables per person vaccinated. The details of the cost were in Supplement Table 1.

2.4 Data analysis and modeling

2.4.1 Data analysis

The collected data were analyzed using an operations research formula for determining service capacity and wait time. SAS software was used to clean all the time-motion study data. We calculate the overall time spent at each step of the process by subtracting the start-point time from the endpoint time. The vaccination capacity evaluation was also based on the data from the time-motion study.

The service capacity per desk can be described as:

$$s^i = \frac{1}{m^i}, \text{ i = registration, vaccination (1.1)}$$

Where the average time $\boldsymbol{m^i}$ for each subtask was calculated. Then, we converted the $\boldsymbol{m^i}$ into service capacity per desk $\boldsymbol{s^i}$. Finally, the service capacity of the subtask was calculated as the product of the number of desks and the $\boldsymbol{s^i}$. The overall service capacity for that clinic depends on the lowest value of the service capacity among subtasks.

The specific calculation formula of utilization rate $\boldsymbol{u^i}$ for each session can be described as:

$$u^i = \frac{r^i}{n^i \times s^i}, \text{ i = registration, vaccination (1.2)}$$

The specific calculation formula of average waiting time $\boldsymbol{E}[\boldsymbol{Tq}]$ for each session can be described as:

$$E[Tq] = \frac{m^i}{n^i} \times \frac{\boldsymbol{u}^{\boldsymbol{i}\sqrt{2(\boldsymbol{n}^{\boldsymbol{i}}+1)}-1}}{1-u^i} \times \frac{C_a^{i\,2} + C_s^{i\,2}}{2}, \mathrm{i} = \text{registration, vaccination} \quad (1.3)$$

Where the utilization rate $\boldsymbol{u}^i$ was calculated by using the arrival rate divided by the service capacity for the subtask, the coefficient of variation for interarrival time $\boldsymbol{C}_{\boldsymbol{a}}^{\boldsymbol{i}}$ was 1, and the coefficient of service time variation $\boldsymbol{C}_{\boldsymbol{s}}^{\boldsymbol{i}}$ was calculated by using the standard deviation of the service time for subtask i divided by $\boldsymbol{m}^i$.

We assessed the whole economic cost (i. e., the cost of all resources needed to implement the vaccination) using a micro-costing method from the health provider's perspective. We kept track of the resources utilized throughout the vaccination process and evaluated the cost of supplies used for COVID-19 vaccination (based on the number of vaccinated people) and the stipends for using a healthcare personnel/nurse (number of the working hour) as variables costs. All expenses were expressed in 2020 USD using OANDA currency conversions (1USD = 6.50 Yuan). The cost analysis was conducted in Excel 2019 (Microsoft, USA). Details of the cost analysis are shown in appendix A.

2.4.2 Optimization modeling

Based on the capacity evaluation results from the time-motion study, a non-linear programming approach was used to determine the optimal capacity planning for both the facility-based and mass vaccination sites through the Excel solver. The objective is to minimize the variable cost of vaccination per day. The variable cost of the vaccination process in each step was calculated from time-motion study collected data.

The decision variables were the number of service desks for registration and vaccination. Constraints include the following: waiting time of each session should not exceed 15 minutes (to avoid potential exposure to positive COVID-19 cases according to the CDC's guidelines [27]), the total number vaccinated per day should exceed the vaccination target $\boldsymbol{p}$, and the arrival rate of each step should be smaller than the service rate. The working hour was 7 hours per day according to the time-motion study.

Additionally, constraints identified at mass vaccination sites were as follows: the arrangement of patient flow for mass vaccination was different from the facility-based vaccination sies where individuals could choose specific vaccination service desk following registration from multiple options. Rather, individuals at mass vaccination sites could only pick between two nearby vaccination stations directly following the registration service desk. Hence, we retained the number of registration service desks and the number of vaccination service desks as 1:2 in our optimization model. Besides, another optimization model without this constraint was built as well (appendix B). The formula of waiting time calculation was as followed:

For facility-based vaccination site:

Objective:

$$\text{Minimize } h\ (n^{registration}c^{registration} + n^{vaccination}c^{vaccination})$$

Subject to:

$$h \times Min[\frac{n^{registration}}{m^{registration}}, \frac{n^{vaccination}}{m^{vaccination}}] \geq p,$$

$\frac{\boldsymbol{m^i}}{\boldsymbol{n^i}} \times \frac{\boldsymbol{u^i}^{\sqrt{2(n^i+1)}-1}}{\boldsymbol{1-u^i}} \times \frac{\boldsymbol{C_a^i}^2+\boldsymbol{C_s^i}^2}{\boldsymbol{2}} \leq 15\ minutes$, i= registration, vaccination,

Where

p: vaccination target for the vaccination site

h: working hours per day

c^i: cost for session i, i= registration, vaccination

$n^{registration}$: number of service desk for registration session

$n^{vaccination}$: number of service desk for vaccination session

For mass vaccination site:

Objective:

Minimize $h\ (n^{registration}c^{registration} + n^{vaccination}c^{vaccination})$

Subject to:

$h \times Min[\frac{n^{registration}}{m^{registration}}, \frac{n^{vaccination}}{m^{vaccination}}] \geq p,$

$\frac{\boldsymbol{m^i}}{\boldsymbol{n^i}} \times \frac{\boldsymbol{u^i}^{\sqrt{2(n^i+1)}-1}}{\boldsymbol{1-u^i}} \times \frac{\boldsymbol{C_a^i}^2+\boldsymbol{C_s^i}^2}{\boldsymbol{2}} \leq 15\ minutes$, i=vaccination, registration,

$\frac{\boldsymbol{n^{registration}}}{\boldsymbol{n^{vaccination}}} = \frac{1}{2},$

2.4.3 Simulation modeling

The discrete-event simulation models were built using the Arena software (a computer-based simulation software). We limited the simulation model scope to the vaccination procedure, using the default data for each vaccination step collected from the time-motion study. The default arrival of people was set at 12 people per arrival every one minute (to be consistent with the vaccination target of 5,000 people vaccinated per day), and the working duration was 7 hours per day. Simulations for the mass vaccination sites investigated the impact of different patient flow arrangements on waiting time. The facility-based vaccination sites were excluded from this simulation because the number of service desks was inadequate to have multiple patient flow arrangements investigated for these sites.

We simulated two mass vaccination sites. The first one is the mass vaccination site A, the number of service desks for each step was determined through the optimization model had the 1:2 constraints on the number of registered service desks and vaccination desks. Another one is the mass vaccination site B, the number of service desks for each step was determined through the optimization model without constraints (appendix B). The overall vaccination process at mass vaccination sites was in three parts: registration, vaccination, and observation. The registration service desks needed health personnel, while the vaccination service desks needed nurses who had vaccination qualifications. The model was divided into four parts: arrival, registration, vaccination, and observation. The "Arrival" block denoted vaccine recipients’ arrival at the facility. In the "Registration" block, vaccine recipients chose to join the shortest queues to wait for their COVID-19 vaccination registration. In the "Vaccination" block, vaccine recipients still selected the vaccination booths with the least number of queued people for vaccination after completing the registration process. Finally, in the "Observation" block, vaccine recipients waited for thirty minutes in an observation room in case of adverse effects onset.

To test the impact of different patient flow arrangements, we conceptualized two distinct ways of patient flow organization: in mass vaccination site A, patients could pick between two nearby vaccination stations directly following the registration service desk as the constraint described previously. At mass vaccination site B, patients could freely choose a vaccination service desk from out of multiple options after registration. We reasoned that there could be variations in outcomes between these two forms of patient flow. The differences in the organization of patient flow between sites A and B translated to changes in the queueing methods. Figure 2-3 shows the two simplified models of different patient flow arrangements. We then conducted a sensitivity analysis to evaluate these optimal operational designs for vaccination sites to improve their operational performance. To assess the effects of different arrival rates, we varied the arrival rates of patients who came into the facility according to the vaccination target (from 5,000 people per day to 6,000).

2.5 Ethical review

The research has been approved by Duke University's Institutional Review Board (IRB Protocol 2021-0227). This study is a sub-study of the program "COVID 19 Vaccination Service Delivery Planning and Technical Assistance in China" funded by the Bill & Melinda Gates Foundation. The Global Health Master's Program at Duke University also supported this study. No personal identified data were collected during the study.

Figure 2. Simplified model of patient flow in mass vaccination site A.

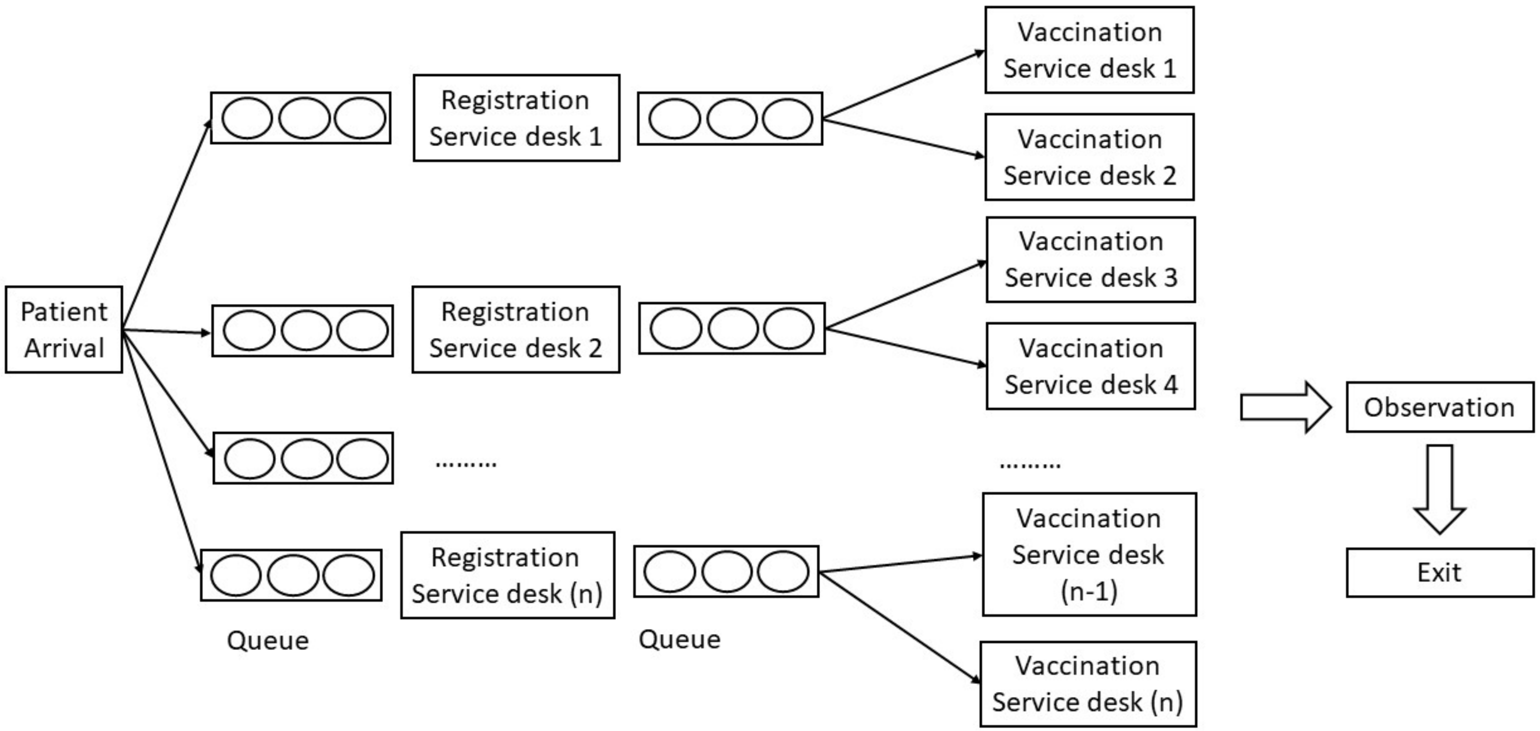
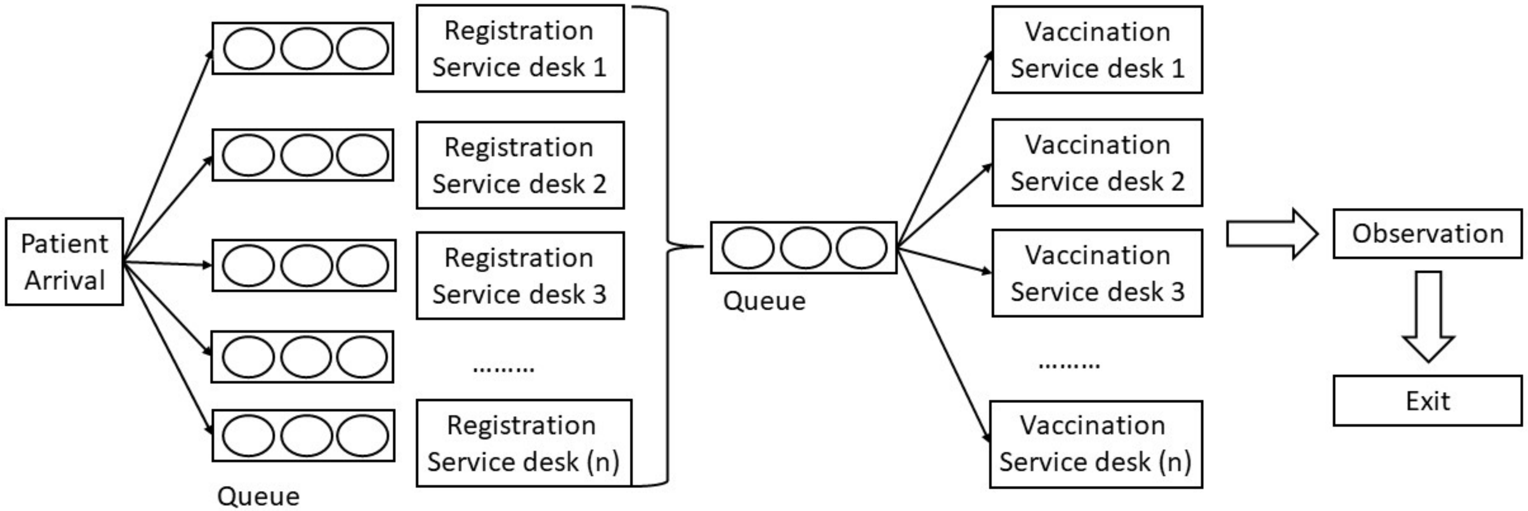


Figure 3. Simplified model of patient flow in mass vaccination site B.



3. Results

3.1 Service capacity and cost of COVID-19 vaccination in real-world health facilities

In total, data from six health facilities were collected from the time-motion study. Table 1 shows the service capacity and the cost for each step at health facilities. The mean time for registration was 69.14 seconds (95% CI: 57.30-80.98) and for vaccination was 97.72 seconds (95% CI: 87.56-107.88). The vaccination was the most time-consuming task of the whole process. The registration capacity was nearly 52 people/hour and 36 people/hour for vaccination. The cost per hour for registration was 8.97 USD and 11.94 USD for vaccination. Details of the cost are shown in appendix A.

Table 1. Service capacity and cost of each subtask in the COVID-19 vaccination process.

	Registration	**Vaccination**
Subtask service capacity evaluation		
Sample size	175	199
Mean time(s)	69.14	97.72
Median time (s)	34.00	76.00
Standard error	79.91	73.15
95% Confidence interval	57.30-80.98	87.56-107.88
Service capacity (people/hour)	52.07	36.84
Cost		
Variable cost* (USD/hour)	8.97	11.94
*This cost didn't include the vaccination consumables cost.		

3.2 Optimal capacity levels of facility-based vaccination sites for different vaccination targets

We determined the capacity level at each step during the vaccination process using the newly developed optimization model. Following the real-world observations, the optimization model was used to find a solution to minimize the cost of achieving vaccination targets, like the number of people vaccinated per day. The optimization was within certain constraints, including the requirement that the waiting time should not exceed 15 minutes for each session and vaccination capacity would reach the set vaccination target per day. Table 2 shows the optimal capacity levels for the facility-based vaccination site calculated using the optimizing model based on the data we collected. Generally, the optimal number of service desks for each session changed with an increase in vaccination targets. The optimal number of service desks for vaccination targets of 500–700 people per day remained at two for registration and three for vaccination. For vaccination target of 800–1,000 people per day, the optimal number of service desks increased to four for vaccination and three for the registration.

The waiting time differed for each session depending on vaccination targets. The waiting time of 13.66 minutes for registration was the highest for a vaccination target of 700 people per day compared to other vaccination targets. The lowest waiting time for registration was 0.81 minutes when the vaccination target was 800 people per day. Waiting time for vaccination was also highest when the vaccination target was 700 people per day and lowest when the vaccination target was 500 people vaccinated per day.

Table 2. Optimal number of service desks for each session under different vaccination targets (Facility-based vaccination site).

Vaccination target (people/day)	500	600	700	800	900	1,000
Waiting time for registration (minutes)	1.06	2.46	13.66	0.81	1.52	3.82
Waiting time for vaccination (minutes)	0.69	1.52	4.75	1.05	2.38	0.78
Optimal number of registration service desks	2	2	2	3	3	3
Optimal number of vaccination service desks	3	3	3	4	4	4
Actual capacity (people/day)	728	728	728	1,031	1,031	1,031
Vaccination variable cost (USD)	624.18	624.18	624.18	873.41	873.41	873.41

3.3 Optimal capacity levels of mass vaccination sites for different vaccination targets

The optimization model was also used to determine the different arrangements for service desks at each step of the vaccination process for mass vaccination sites. The only difference in this model was the inclusion of the real-world constraint that registration service desks have to be half the number of vaccination service desks.

The optimal number of service desks for each session increased with every increase in vaccination targets (Table 3). When the vaccination target was 5,000 people per day, the optimal number of service desks was 14 for registration and 28 for vaccination. The optimal number of service desks changed as the increased vaccination targets. The waiting time for registration and vaccination varied with the different vaccination targets. Results from optimization models for mass vaccination site without the real-world constraint is in appendix B.

Table 3. Optimal number of service desks for each session under different vaccination targets (Mass vaccination site).

Vaccination target (people/day)	5,000	6,000	7,000	8,000	9,000	10,000
Waiting time for registration (minutes)	3.73	1.82	1.16	0.83	3.46	1.78
Waiting time for vaccination (minutes)	1.48	1.41	1.37	1.34	1.52	1.48
Optimal number of registration service desks	14	17	20	23	25	28
Optimal number of vaccination service desks	28	34	40	46	50	56
Actual capacity (people/day)	5,102	6,196	7,289	8,383	9,112	10,205
Vaccination variable cost (USD)	4,954.29	6,015.92	7,077.56	8,139.19	8,846.95	9,908.58

3.4 Patient flow arrangement at mass vaccination sites

The discrete event simulation models were built to simulate the different mass vaccination sites using diverse patient flow arrangements and used to explore the impact of various patient flow arrangements. Details of the default parameters used in the simulation model are outlined in appendix C.

The total number of people out of the mass vaccination site A was 4,929. It took an average of 5.52 minutes for an individual to leave the vaccination site. The waiting time for registration was 3.11 minutes, and 0.11 minutes for vaccination. No one was required to wait in the registration or vaccination queue. The utilization rate for healthcare personnel was 0.97, and for nurses, it was 0.68. The cost of operating the vaccination facility was 4,902.30 USD.

For the mass vaccination site B, we simulated the model using the optimal number of service desks, which was 14 for registration and 20 for vaccination, calculated from the previous optimizing model. The total number of people out was 4,897. The average time for an individual left the vaccination site was 6.68 minutes. The average waiting time for the registration queue was 2.89 minutes and 1.91 minutes for the vaccination queue. The utilization rate of healthcare personnel was 0.97 and 0.95 for nurses. The total cost for operating the mass vaccination site B was 4,222.66 USD. The comparison of operational performance for mass vaccination site A and B shows in Table 4.

Table 4. Comparison of operational performance for mass vaccination site A and B.

Type of vaccination sites	**Mass vaccination site A**	**Mass vaccination site B**
Number of service desks (registration)	14	14
Number of service desks (vaccination)	28	20
Total number of people out	4,929	4,897
Cost of operating the vaccination facility	4,902.30 USD	4,222.66 USD

Average time for an individual leaves the vaccination site	5.52 minutes	6.68 minutes
Waiting time for registration	3.11 minutes	2.89 minutes
Waiting time for vaccination	0.11 minutes	1.91 minutes
Utilization rate for healthcare personnel	0.97	0.97
Utilization rate for nurses	0.68	0.95

Additionally, the effect of varied arrival rates on the average waiting time for individuals at mass vaccination site A and B was investigated (figure 4). We observed a decreasing trend in the average waiting time for the vaccination site as the arrival rate fell. In comparison to mass vaccination site A, mass vaccination site B had a higher average wait time.

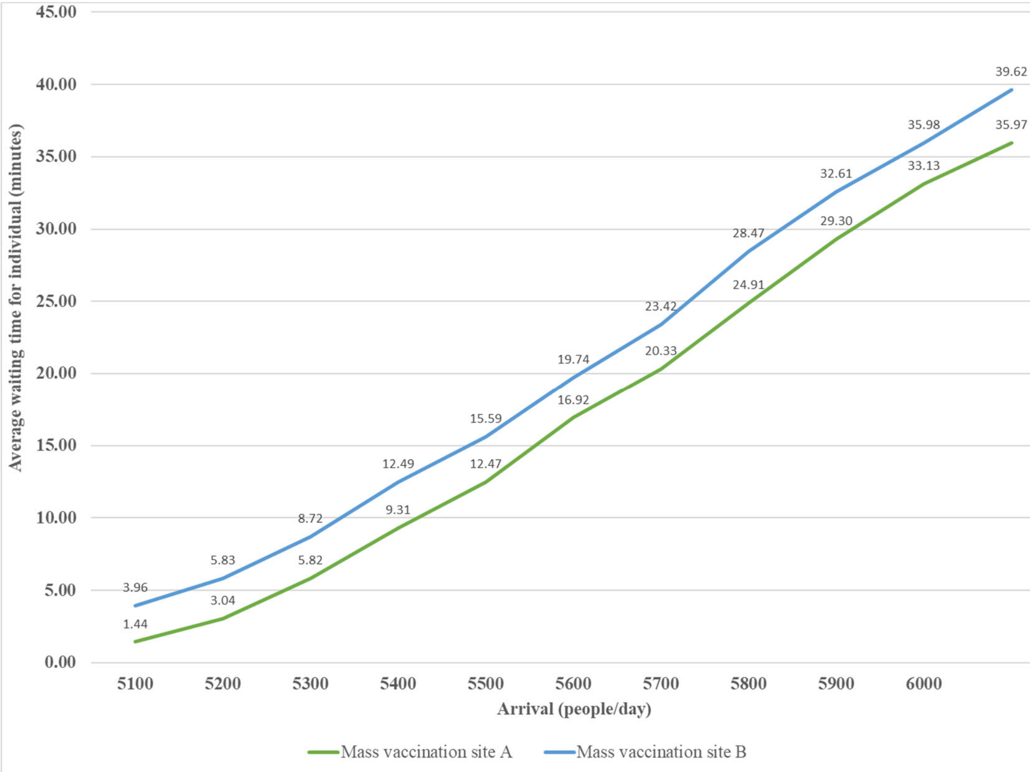


Figure 4. The impacts of varied arrival rate on average waiting time in each mass vaccination site.

4. Discussion

4.1 Discussion on the key findings

This study applied the time-motion method, optimization models, and simulation models to develop strategies for improving future COVID-19 vaccination site planning. We used the time-motion study to determine the actual duration of vaccination processes, and optimization models helped identify the optimal capacity level of different vaccination sites for different targets and optimal ways to reduce the cost. This study also determined the potential impacts of different patient flow arrangements on mass vaccination sites through simulation modeling.

The results from the time-motion study suggest that vaccination is the most time-consuming part of the process. This finding is consistent with the results observed by Quach et al. [28] but differs from the findings of Mokiou et al. [16] and Bhattacharya et al. [29]. However, this observation is reasonable as their definitions of pre-vaccination activities were different. Despite the differences in the types of vaccines, our observed vaccination processing time is similar to that reported by previous studies [16, 28, 29]. We believe this is because the steps in the vaccination process are similar in both studies. Overall, the time-motion study provides the time required for each step of the COVID-19 vaccination, which informs researchers and policymakers in estimating the current COVID-19 vaccination capacity of health facilities.

The optimization models established in this study could be valuable tools for policymakers to optimize the capacity level of vaccination sites for different targets. Our study extends the existing literature by developing optimization models which ensure that pre-determined vaccination targets are achieved with minimal expense while reducing people's risk of cross-infection at vaccination sites. Although Abay et al. [30] developed models to facilitate the capacity planning for vaccination sites, they didn’t consider reducing the risk of cross-infections during the vaccination process in their models. In another study, Beeler et al. only evaluated the flu transmission risk in their simulation but didn't try to reduce the infection risk in their model [31]. Given the high infectiousness of COVID-19 [32], it is critical to consider reducing the risk of infection when planning the capacity for COVID-19 vaccination sites. Meanwhile, this optimization model can be reformulated to maximize the total number of vaccinations under given resources, which increases the feasibility of the tool to fulfill the policymakers’ real-world requirements.

We also found that compared to facility-based vaccination sites, a single mass vaccination site would require fewer service desks than multiple facility-based vaccination sites to achieve a certain vaccination target. This may be due to the pooling effects when the mass vaccination site pooled the service desks together, which may improve the operational performance [33] and hence require fewer service desks. Therefore, we would like to suggest an area that doesn’t have enough facility-based vaccination sites allocate the human resources to build a mass vaccination site for mass vaccination. However, this may only suit areas that have enough space and other equipment to build a mass vaccination site. If an area needs to vaccinate a large number of people in a short period and lacks enough medical personnel to operate many separate facility-based vaccination sites, we would suggest policymakers build a mass vaccination with fewer human resources required compared to using multiple facility-based vaccination sites.

Meanwhile, we used the simulation models to compare two patient flow arrangements at mass vaccination sites. Our simulation results suggest that mass vaccination site B is more flexible. It has the flexibility to arrange the number of vaccination service desks from 20 to 28. In real-world vaccination site planning, it depends on whether the policymaker prefers less waiting time or less expenditure. To reduce waiting time, governments might consider expanding the number of service desks. If policymakers want to reduce costs, they may apply the present setup estimated by the optimization models at a cost of a long waiting time. However, considering the complexity of reality, this simulated outcome can only serve as some reference for patient flow arrangements at mass vaccination sites. Besides, we should note that the waiting time estimated in this model represents an idealized situation, which has several presumptions. Policymakers should take these presumptions into account when planning for real-world vaccination activities.

4.2 Study strengths and limitations

This study has several strengths. First, this study provides on-site observational data on vaccination of COVID-19, which provides a reference for the current capacity and patient flow arrangement of different sites for future COVID-19 vaccination. Second, our model framework also considered the risk of COVID-19 infection in vaccination sites, with none of the waiting times of our vaccination design exceeding 15 minutes, which ensures safety during the vaccination process [27]. Third, this study extended the existing literature by identifying trade-offs between facility-based sites and mass vaccination sites for the planning COVID-19 vaccination [34]. The result of this study can provide some references for future vaccination sites planning.

The study has several limitations. First, we did not document the data on patient-arrival rates in this study. However, we conducted a sensitivity analysis for the simulation model to evaluate the impacts of different arrival rates on individuals' waiting time in the vaccination site. Second, the assumed scenario is the most idealized scenario, i.e., no breaks and rotations were required for medical personnel. Hence, the personnel cost in actual operation may be higher than the estimated value in this study. Third, this study didn't consider the impacts of other factors like the difference in service time between the elderly and children at the time of vaccination [35], etc. Therefore, future studies should consider further investigating the effects of these other factors.

5. Conclusion

This research developed a modeling framework that incorporated the optimization models and discrete event simulation models to aid in the planning of the COVID-19 vaccination site. Our results suggest our modeling framework is useful in vaccination site operational design in terms of optimizing the capacity level, finding out the trade-off point for vaccination site planning, and reducing the cost for operating the vaccination sites, which provides references for researchers and policymakers to plan for future COVID-19 vaccination sites.

Appendix A Health facility vaccination cost evaluation

The total variable cost was calculated combined with three parts: the cost of nurse per hour, the cost of healthcare personnel per hour, and the cost of vaccination consumables per person vaccinated. The details of the cost were in Supplement Table 1.

The overall compensation for nurse and healthcare personnel per day was 61.57 USD, calculating as working 7 hours a day, the compensation for nurse and healthcare personnel per hour was 8.80 USD. The equipment cost for a nurse per day was 22.01 USD and 1.23 USD for healthcare personnel, due to the different COVID-19 prevention requirements. The total cost for using a nurse per day was calculated by adding the personnel compensation and the personnel protective equipment cost, which was 83.59 USD. The total cost for using a healthcare personnel per day was calculated the same as the nurse one, which was 62.81 USD. Calculating as working 7 hours a day, the unit cost of a nurse per hour is 11.94 USD and 8.97 for healthcare personnel.

For the vaccination consumables, the vaccinated individuals will spend 0.34 USD, fees included the syringe, informed consent letter, vaccination certificate, vaccination notification form, and leaflet.

Supplement Table 1. Cost summary of the vaccination process

Personnel cost	**Daily compensation (USD)**	**Number of hours per day**	**Cost per hour (USD)**
Nurse	61.58	7	8.80
Healthcare personnel	61.58	7	8.80
Personnel protective equipment cost	**Unit price (USD)**	**Number of units per people**	**Cost per use (USD)**
For Nurse			
Face Screen	0.15	1	0.15
Protective caps	0.15	2	0.31
N95 mask	1.54	2	3.08
Isolation gown	7.70	2	15.39
Surgical gloves	0.77	4	3.08
Cost per nurse			22.01
For healthcare personnel			
Protective caps	0.15	2	0.31
Surgical mask	0.15	2	0.31
Plastic gloves	0.15	4	0.62
Cost per healthcare personnel			1.23
Variable cost			
Unit cost per day (Nurse)			83.59
Unit cost per day (Healthcare worker)			62.81
Unit cost per hour (Nurse)			11.94
Unit cost per hour (Healthcare worker)			8.97
Vaccination consumables cost*	**Unit price (USD)**	**Number of units per people**	**Cost per use (USD)**
Syringe	0.10	1	0.10
Informed consent letter	0.15	1	0.15
Vaccination certificate	0.02	1	0.02
Vaccination notification form	0.02	1	0.02
Leaflet	0.05	1	0.05
Cost per people vaccinated			0.34

*This cost didn't consider the cost of vaccine purchase, transportation and storage.

Appendix B The optimization model for mass vaccination site without the real-world constraint

Based on the capacity evaluation results from the time-motion study, a non-linear programming approach was used to determine the optimal capacity planning for both the facility-based and mass vaccination sites through the Excel solver. The objective is to minimize the variable cost of vaccination per day. The variable cost of the vaccination process in each step was calculated from time-motion study collected data.

The decision variables were the number of service desks for registration and vaccination. Constraints include the following: waiting time of each session should not exceed 15 minutes (to avoid potential exposure to positive COVID-19 cases according to the CDC's guidelines [27]), the total number vaccinated per day should exceed the vaccination target $\boldsymbol{p}$, and the arrival rate of each step should be smaller than the service rate. The working hour was 7 hours per day according to the time-motion study.

The formula of waiting time calculation was as followed:

For mass vaccination site:

Objective:

Minimize $h\ (n^{registration}c^{registration} + n^{vaccination}c^{vaccination})$

Subject to:

$h \times Min[\frac{n^{registration}}{m^{registration}}, \frac{n^{vaccination}}{m^{vaccination}}] \geq p,$

$\frac{m^i}{n^i} \times \frac{u^{i\sqrt{2(n^i+1)}-1}}{1-u^i} \times \frac{{C_a^i}^2+{C_s^i}^2}{2} \leq 15\ minutes$, i=vaccination, registration.

The result of the optimization model is in Supplement Table 2.

Supplement Table 2. Optimal number of service desks for each session under different vaccination target (Mass vaccination site without real-world constraint).

Vaccination target (people/day)	5,000	6,000	7,000	8,000	9,000	10,000
Waiting time for registration (minutes)	3.73	1.82	1.16	0.83	3.46	1.78
Waiting time for vaccination (minutes)	1.43	1.16	0.97	3.53	2.40	1.79
Optimal number of registration service desks	14	17	20	23	25	28
Optimal number of vaccination service desks	20	24	28	31	35	39
Actual capacity (people/day)	5,102	6,196	7,289	8,383	9,112	10,205
Vaccination variable cost (USD)	4,226.52	4,749.21	5,271.90	5,711.01	6,170.91	6,693.60

Appendix C The default parameters of the simulation models

The default parameters of the simulation models were showed in Supplement Table 3.

Supplement Table 3. The default parameters of the simulation models.

Session	Item	Value	Source
Arrival	Arrival	12 people per minutes	Assumption
Registration	Number of healthcare personnel	14	Optimization model
Vaccination	Number of nurses	28	Optimization model
Registration	Healthcare personnel cost	11.94$ per hour	Time-motion study
Vaccination	Nurse cost	8.97$ per hour	Time-motion study
Vaccination	Vaccination consumables cost	0.34$ per use	Time-motion study
Observation	Chance of allergic reaction	0.0011	[36]
Registration	Processing time per people	exponential distribution (69.137) s	Time-motion study
Vaccination	Processing time per people	exponential distribution (96.33) s	Time-motion study
Observation	Time per people	30 minutes	[37]
Observation	Emergency reaction time	15 minutes	[38]

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