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DETERMINING THE IMPACT OF FACILITY LAYOUT METHODS ON WALK-IN COVID-19 VACCINE CLINICS: A THEORETICAL EXPLORATION

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ABSTRACT

Ensuring safety and public health is a paramount concern in mass vaccination against contagious respiratory infections. This study examines the effects of layout methods and path routing decisions on average patient travel distance (TD) and time-in-system (TIS) within the context of a theoretical mass vaccination clinic. Two distinct layout methods, Perimeter and Serpentine, are evaluated in conjunction with two path routing conditions, Cyclical and Unidirectional. Employing discrete-event simulation, the study investigates multiple patient turnouts and clinic operational hours. The results reveal the significant impact of layout on average TD, underscoring the heightened efficiency of the Perimeter layout and Unidirectional path. Furthermore, the findings highlight the significant effect of layout method on TIS when considering optimal staffing configurations. Conversely, the analysis indicates that path directionality does not exert a statistically significant effect. This study emphasizes the critical role of layout design in optimizing vaccination clinics for efficiency and effectiveness.

1 INTRODUCTION

The COVID-19 pandemic has caused 660 million confirmed cases and 6.7 million deaths as of the beginning of 2020, and the numbers are still rising (World Health Organization 2020). The most effective method for preventing disease and controlling virus transmission is vaccination (Frederiksen et al. 2020). Vaccination clinics run by the public health department (PHD) are intended to give immunizations to large groups of people as quickly and safely as possible. In addition to monitoring vaccination uptake and safety, these PHD programs must properly and effectively store, distribute, assign, and manage vaccines and related materials (Centers for Disease Control and Prevention 2023). Large-scale vaccination clinics were critical in hastening the effective roll-out of COVID-19 vaccinations in the face of 1) limited vaccine supply, 2) competing medical resources, and 3) vaccination priority based on age or high-risk status (Goralnick et al. 2021). Although PHD-led vaccination clinics are not a brand-new idea (Klaiman et al. 2013; Porter et al. 2011), the COVID-19 pandemic offered practical difficulties for its implementation.

Meeting the increased demand for vaccination by having a high patient throughput is one of the main objectives of PHD-led vaccination clinics. To do this, clinic planners use a number of tools to organize and manage clinics. The Centers for Disease Control and Prevention (CDC) in the US offer instructions on how to organize and be ready for these kinds of clinics. Only a few papers have emphasized the effectiveness of vaccination clinic sites (Andrade et al. 2021; Moyce et al. 2021). In order to address concerns about how to set up a PHD-led vaccination center during the COVID-19 pandemic, recent research examined the prior experiences of PHD-led vaccination centers (mostly influenza), stressing the key organizational factors that should be taken into account while planning (Gianfredi et al. 2021). Despite the fact that these resources

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might be useful to planners, none of them offer quantitative proof of certain attributes across several clinics that encourage high throughput.

In order to enhance patient care, boost system productivity, and raise service quality, interdisciplinary approaches to healthcare make use of partnerships between nursing and engineering (Zhou et al. 2021). When trying to make healthcare systems better, engineering tools are frequently used. Models used in the healthcare industry might be useful in assessing staff productivity. A time study is one of these tools, in which an observer logs the motions and length of tasks (Lopetegui et al. 2014). The effectiveness of patient waiting times (Aburayya et al. 2020), nursing care (Yen et al. 2018), clinical workflow (Young et al. 2018), and prescription delivery (Hond et al. 2021) have all been studied using time studies in the medical field. Queuing theory, a similar concept, is employed in healthcare systems as a means of estimating patient arrival processes, access times, and characteristics of how they are moved along the line. These guidelines have been used to reduce waiting times in outpatient settings (Peter and Sivasamy 2021) and emergency departments (Litvak et al. 2001). They also have practical implications for staffing and controlling patient flow in an outpatient or clinic context since they may be used to calculate the number of nurses needed to provide patient care (Yankovic and Green 2011).

There have been a few published papers on the use of industrial engineering techniques, including discrete-event simulation (DES), to build a mass walk-in COVID-19 vaccination clinic (Valladares et al. 2022). For example, Asgary et al. (2021) used DES and agent-based modelling methods for designing the drive-through mass vaccination clinics, and Wood et al. (2021) implemented operational research to design the COVID-19 vaccination centers efficiently. The majority of studies focus on enhancing contact tracing strategies to reduce the spread of COVID (Braune et al. 2021) and regulating hospital protocols during a spike in COVID cases (Bhandari et al. 2021), or on determining how long a diagnostic test could take (Majedkan et al. 2020). A few of them focus on the design and improvement of COVID-19 vaccination clinics employing a multidisciplinary approach and effort between nurses and engineers to build a patient-centered vaccination clinic with quality improvement measures used by engineering (Valladares et al. 2022). Digital twins are developed to integrate physical and virtual systems and to map patient flow in real-time for a sustainable and dynamic vaccination center. In this way, using a discrete-event simulation model integrated into a mobile application, time measures and indicators can be computed to find problems, run the virtual model to solve them, and replicate improvements in real life (Pilati et al. 2021).

This study utilizes computational simulation analysis to investigate the relationship between facility layout planning and the performance of vaccination systems using discrete-event simulation (DES). The objective is to explore whether the layout of a clinic has an impact on the performance of the vaccination system. The analysis involves creating theoretical vaccination systems and examining the effects of different facility layout methods and patient path directionality on two performance measures: patient time-in-system (TIS) and patient travel distance (TD). Rather than seeking an optimal layout strategy, the focus is on understanding the relationships between layout and performance and identifying the systems that yield the best performance metrics. The research questions in this study are: 1) What is the impact of layout methods and path directionality on performance measures, specifically Time-in-System (TIS) and Travel Distance (TD)? 2) Are there statistically significant differences in TIS and TD observed between different layout methods and path routings? 3) What is the best design?

2 METHODS AND ASSUMPTIONS

2.1 Conceptual Modelling

This study utilizes theoretical eight-step vaccination system models that are representative of the mass vaccination process implemented in Omaha, NE. The eight-step vaccination system consists of (i) an appointment check process, (ii) greeter 1, (iii) a clinical check process, (iv) greeter 2, (v) vaccination process, (vi) sticker distributer, (vii) observation process, and (viii) check-out. In this system, a patient arrives and enters the queue for the appointment check process. When patients complete the appointment check process, a greeter worker assists %95 of them to move to the clinical check process. A total of 5% of the patients exit the system due to appointment-related issues, while another 5% of patients opt to leave the system without receiving the vaccine due to clinical problems. After completing the clinical check process, the remaining patients proceed to the vaccination tables. Once vaccinated, patients receive a sticker from a distributor worker and proceed to an observation area where they are required to sit for approximately 15 minutes. Patients may then proceed to check-out and exit the system if they are feeling well. In this system, queues are managed in a manner that restricts patient flow if all staff members are occupied with other patients. In such cases, patients are required to wait at the waiting queues until a staff member becomes available to attend to them. The process flow chart for the system is shown in Figure 1.

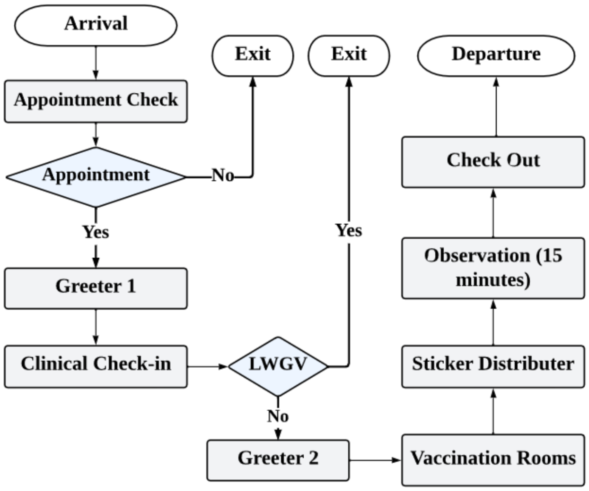


Figure 1: Process flow chart for an eight-step mass vaccination system (LWGV stands for left without getting a vaccine).

In this analysis, two independent variables were examined: patient path routing and the layout of the vaccination process equipment. The study focused on monitoring two dependent variables: patient time-in-system and patient travel distance. The control variables included patients' turnouts per day (500, 1000, 2000) and operational hours per day (8, 10, 12), representing the clinic sizes. The aim was to observe how the dependent variables varied across different clinic sizes. Comparisons were conducted for patient travel distance and time-in-system between layouts and path directionalities while keeping the clinic's operational hours constant. Additionally, the impact of optimal and constant staffing scenarios was assessed. The room size was kept constant, with a 1000 sqft room serving as the model for the theoretical system. This rigorous analysis contributes to a comprehensive understanding of the factors influencing vaccination clinic performance.

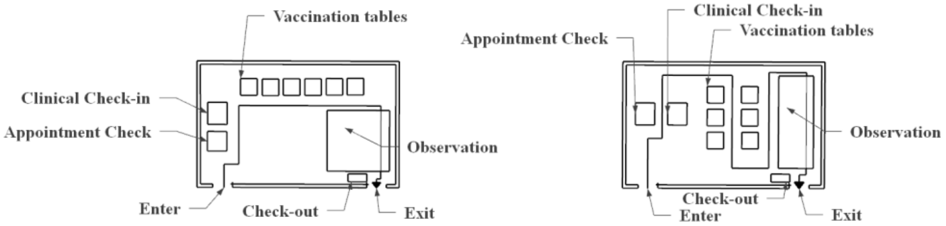
2.2 Layout and Path Routing

This study investigated two distinct table and equipment placements within the vaccination clinic setting (Figure 2). One configuration resembled the observed vaccine clinic in Omaha, NE, with stations positioned along the walls, similar to the Perimeter layout method (Figure 2, a and c). The other layout followed the Serpentine layout method commonly utilized in facility layout planning (Botsali and Peters 2005; Zijlstra and Mobach 2011). In the Serpentine layout, the patient path formed an "S" shape through the vaccination system, with stations positioned on the left and right sides of the path (Figure 2, (b) and (d)). Each layout was further modeled with two path directionalities: 1) cyclical and 2) unidirectional. In the cyclical path, patients entered and exited through the same door, while in the unidirectional path, patients entered through a designated entrance door and exited through a designated exit door located at the opposite end of the wall (McCool-Guglielmo et al. 2022). The placement of the doors was kept consistent throughout the systems.

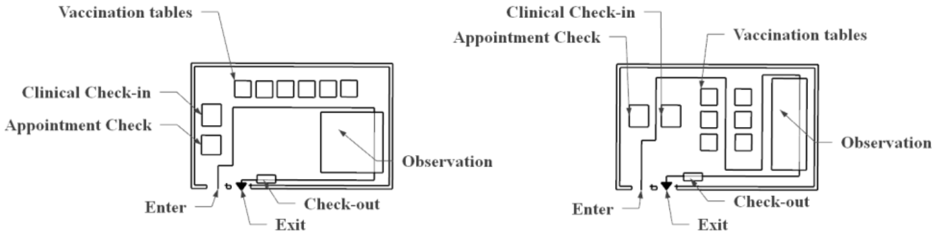
2.3 Assumptions

Assumptions regarding the setup and analysis of theoretical systems included the following:

(1) All the patients move according to the process flow chart. Therefore, patients do not have to walk by or pass-through vaccine stations to access the check-in stations.
(2) Patients are served in the order they enter the appointment check queue.
(3) Patient travel path begins at the entry door and ends at the exit door; therefore, the only travel distance considered in this analysis occurs within the vaccination process location.



(a) Unidirectional Perimeter Layout Method (b) Unidirectional Serpentine Layout Method



(c) Cyclical Perimeter Layout Method (d) Cyclical Serpentine Layout Method

Figure 2: Perimeter and Serpentine layout methods with path directionality.

2.4 Model Inputs

The theoretical models utilized in this study were developed based on estimated processing times derived from observations of walk-in vaccination clinics during the COVID-19 vaccination campaign in 2021 in Omaha, NE. These processing times, primarily focused on clinical check-in, vaccination, and observation stations, were manually observed and collected. Data collection involved the use of a timer as the primary tool, allowing observers to track multiple patients simultaneously and record processing times in a tabular format. Rigorous training was provided to the data collection observers to ensure adherence to a standardized approach, minimizing potential errors. Specifically, the timer was initiated upon the patient's arrival at the check-in station and stopped when the patient began their departure from the station. The processing times, represented by triangular and uniform distributions for all stations, are detailed in Table 1. The assumed constant staffing scenario for the appointment check, clinical check, and vaccination stations was set at 3, 6, and 12 servers, respectively. To establish balanced staffing levels, an optimization process was conducted, considering 100 staffing scenarios (Ahmadi and Lather 2021). The outcomes of this optimization process, presenting the optimal staffing configurations, are presented in Table 2.

Table 1: Processing times (Minutes).

Servers	Appointment Check	Clinical Check	Vaccination	Sticker Giver	Observation	Check Out
Processing Time	Triangular [0.5,1.5,2.5]	Triangular [2,3,4]	Triangular [4,6,9]	Triangular [0.25,0.5,0.75]	Uniform [14,16]	Triangular [0.5,1,1.5]

Table 2: Optimal staffing for all clinic turnouts and operational hours.

Clinic size	500			1000			2000		
	8hr	10hr	12hr	8hr	10hr	12hr	8hr	10hr	12hr
Appoint. check	2	2	2	4	3	3	8	6	5
Clinical check	4	3	3	7	6	5	14	12	10
Vaccination	7	6	5	14	11	10	28	23	19

2.5 Model Coding and Experimental Design

All layout models (n = 4) were created in SketchUp®. Initially, the models serving as a starting point for the vacant rooms were generated. Then, appointment check, clinical check, vaccination, observation, and check-out stations were placed based on the two considered layouts. Discrete-event simulation using Simio™ simulation software was used to simulate the outcomes of each hypothetical system. The assumptions outlined in Conceptual Modelling were used to generate each of the models. From the vaccine stations, patients traveled on a path to a *transfer node* before moving to the observation area. For each of the appointment check, clinical check, and vaccination stations, the number of staff were assigned as capacity, and all the vaccination stations were modeled in Simio as an individual server.

Paths were created from the arrival source to the sink to model the patient walking from the arrival to the exit sink. The layout design from SketchUp® was imported into Simio™, and pathways were overlaid onto the layout. For each combination being tested, a dedicated simulation file was created. The total patient turnout and operational time of the clinic were variables input to model the systems. Individual scenarios were conducted for varying levels of staffing in the appointment check, clinical check, and vaccination stations. This approach aimed to determine the optimal staffing configuration for each system, allowing for a comparison of performance measures across different scenarios. A hypothesis assumed a constant number of staff across all systems, enabling the comparison evaluation of performance metrics with balanced staffing levels for each system.

An estimated scheduled arrival pattern with a random discrete distribution was considered based on the total number of patients and operational time of each clinic size. To minimize variations in different scenarios and ensure the reproducibility of results, a distinct common random number (CRN) was established for every variable. This CRN ensured that the randomness in processing time remained consistent across all replications and simulations. A subset of scenarios that completed the service of the last patient within a reasonable amount of time was tested for each control variable. The responses tracked within Simio™ were average total travel distance (TD) by patients within the system, and average time-in-system (TIS).

This research aims to explore whether the layout of vaccine clinic equipment and path directionality have an effect on vaccination system performance. It is hypothesized that layout and path directionality does have a significant effect on vaccination system performance. DES modeling was used to monitor the effects of the various systems on the performance metrics. Simio™ outputs the mean value and half-width for each scenario within each system, and using these values, a confidence interval with a 95% level of confidence was calculated for the average patient TIS for two scenarios of optimal and constant number of servers in each station, and average patient TD. A t-test was used to compare the means of the systems within each clinic size to determine if they were statistically different.

3 RESULTS

3.1 Average Total Patient Travel Distance

The confidence intervals with a significance level of $\alpha = 0.05$ for the average total patient TD at all turnout levels are shown in Table 5. According to the table, all systems have confidence intervals around the mean TD which do not have overlapping. This suggests that there are significant differences in TD among the systems analyzed. The travel distances (TD) are normalized by dividing the total travel distance by the number of patients in the system to show the average TD for one patient in the system, regardless of the number of patients and hours of clinic operation. The findings suggest that the number of patients and clinic operational hours do not exert a statistically significant impact on patient travel distance.

3.1.1 TD and Layout Methods

When the path directionality is held constant, the effect of the layout on the total average patient TD can be detected. The analysis reveals significant disparities in patient travel distance (TD) between the two layout methods across all patient turnouts and operational hours (Table 3), underscoring notable differences in their effects. This is further supported by Figure 3b, which demonstrates that the average patient TD increases when the layout adopts a Serpentine configuration for all models and system settings.

3.1.2 TD and Path Directionality

When the layout method is held constant, the effect of the path routing on the total average patient TD can be determined. The differences in total average patient TD in meter for each layout is demonstrated in Table 4 for all turnout levels. There were no significant differences in average TD between the cyclical and unidirectional path routings for any of the layout methods at any clinic size cases.

Table 3: Differences in average TD by layout method (Meters).

Turnout	System Settings	Layout method comparisons (Perimeter and Serpentine) for three clinic operational hours		
No. of Patients	Path Routing	8 hours	10 hours	12 hours
500	Cyclical	33.94***	34.31***	34.56***
500	Unidirectional	39.94***	36.71***	37.77***
1000	Cyclical	33.98***	34.33***	34.58***
1000	Unidirectional	38.26***	39.06***	37.29***
2000	Cyclical	34.02***	34.37***	34.61***
2000	Unidirectional	36.90***	35.58***	39.40***

Note. Significance: * p < 0.05, ** p < 0.01, *** p < 0.001, na = not statistically different

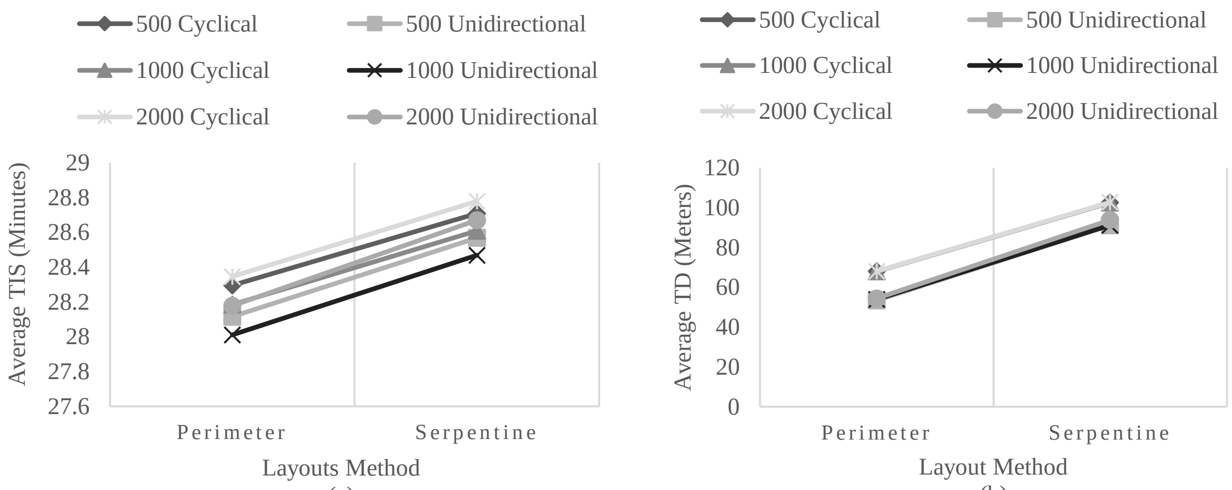
Table 4: Differences in average TD by path directionality (Meters).

Turnout	System Settings	Path directionality comparisons (unidirectional and cyclical) for three clinic operational hours		
No. of Patients	Layout Method	8 hours	10 hours	12 hours
500	Perimeter Layout	15.40	14.44	14.56
500	Serpentine Layout	9.396	12.08	11.35
1000	Perimeter Layout	13.68	14.90	14.07
1000	Serpentine Layout	9.409	10.18	11.36
2000	Perimeter Layout	13.81	13.28	13.62
2000	Serpentine Layout	10.93	12.06	8.830

Note. Significance: * p < 0.05, ** p < 0.01, *** p < 0.001, na = not statistically different

3.2 Average Patient Time-In-System (TIS)

The results depicted in Figure 3a, representing one of the clinic's operational hours, reveal an increase in the average patient time-in-system (TIS) with the implementation of the Serpentine layout across all models



(a) (b)

Figure 3: (a) Average patients TIS and (b) TD over layouts for 12 hours of operational time.

and system settings. Visual summaries in the form of Figure 4 through Figure 6 provide an overview of the data distribution, capturing measures of central tendency, spread, and skewness. Additionally, Table 5 presents the confidence intervals for the average patient TIS, considering both optimal and constant staffing, across all patient turnout levels. Notably, the table demonstrates non-overlapping confidence intervals around the mean TIS for systems with optimal staffing, signifying significant differences. Further elaboration on these significant differences is provided in subsequent sections.

3.2.1 TIS and Layout Methods

When the path directionality is held constant, the effect of layout on the average patients TIS can be explored. The differences in average TIS in minutes by layout when controlling path directionality are shown in Tables 6 for all turnout levels. If the value is positive, it means that the overall TIS has gone up from the first layout method to the second. Conversely, if the value is negative, it indicates a decline in the total TIS between the first and second layout methods.

There are significant differences in TIS between the Perimeter and Serpentine layouts given optimal staffing at all patient turnouts, regardless of path directionality. The systems utilizing the Perimeter layout had a significantly lower average TIS than those utilizing the Serpentine layout for the cyclical path and the unidirectional path. No significant differences were found between the two layout methods when the staffing levels were kept constant. Additionally, as the patient turnout increased, the average TIS for the constant staffing configuration showed a corresponding increase (Table 5), indicating an imbalance between supply and demand. While all systems effectively processed lower levels of turnout, at a patient turnout of 2000, the average TIS exceeded three hours, highlighting the potential occurrence of long queues in any of these systems when the patient turnout approaches 2000 individuals.

3.2.1 TIS and Path Directionality

When the layout method is held constant, path directionality on the average patient TIS can be explored. The differences in average TIS in minutes by path directionality for each system when controlling for layout are shown in Table 7. No statistically significant differences in average patient TIS were observed between the cyclical and unidirectional paths for any of the layout methods, regardless of staffing levels and patient turnouts.

Table 5: Average patient time-in-system and travel distance.

No. of Patients	Clinic Hours	Layout Method	Path Directionality	Average TIS (Min.) 95% CI (Left= Optimal Staff Scenario, Right= Constant Staff Scenario)		Average TD (Meters) 95% CI
500	12	Perimeter	Cyclical	(28.2587, 28.3322)	(26.7638, 26.7930)	(67.9284, 67.9941)
500	12	Perimeter	Unidirectional	(28.0790, 28.1524)	(26.5840, 26.6132)	(53.3777, 53.4293)
500	12	Serpentine	Cyclical	(28.6713, 28.7462)	(27.1913, 27.2195)	(102.473, 102.572)
500	12	Serpentine	Unidirectional	(28.5310, 28.6059)	(27.0509, 27.0792)	(91.1258, 91.2142)
500	10	Perimeter	Cyclical	(28.5435, 28.6294)	(26.8487, 26.8796)	(67.4502, 67.5282)
500	10	Perimeter	Unidirectional	(28.3639, 28.4498)	(26.6691, 26.6999)	(53.0140, 53.0753)
500	10	Serpentine	Cyclical	(28.9851, 29.0700)	(27.2736, 27.3045)	(101.743, 101.859)
500	10	Serpentine	Unidirectional	(28.8351, 28.9200)	(27.1236, 27.1545)	(89.7056, 89.8086)
500	8	Perimeter	Cyclical	(28.8636, 28.9654)	(27.0603, 27.0971)	(66.7346, 66.8295)
500	8	Perimeter	Unidirectional	(28.6700, 28.7719)	(26.8668, 26.9035)	(51.3476, 51.4206)
500	8	Serpentine	Cyclical	(29.2911, 29.3952)	(27.4869, 27.5258)	(100.650, 100.792)
500	8	Serpentine	Unidirectional	(29.1728, 29.2768)	(27.3685, 27.4074)	(91.2610, 91.3893)
1000	12	Perimeter	Cyclical	(28.1596, 28.2096)	(27.6412, 27.6806)	(67.9649, 68.0215)
1000	12	Perimeter	Unidirectional	(27.9860, 28.0359)	(27.4675, 27.5070)	(53.8982, 53.9431)
1000	12	Serpentine	Cyclical	(28.5850, 28.6330)	(28.0678, 28.1062)	(102.530, 102.615)
1000	12	Serpentine	Unidirectional	(28.4446, 28.4927)	(27.9274, 27.9658)	(91.1763, 91.2524)
1000	10	Perimeter	Cyclical	(28.6342, 28.6945)	(28.4443, 28.4960)	(67.4975, 67.5666)
1000	10	Perimeter	Unidirectional	(28.4489, 28.5093)	(28.2591, 28.3107)	(52.6010, 52.6549)
1000	10	Serpentine	Cyclical	(29.0630, 29.1207)	(28.8733, 28.9259)	(101.811, 101.915)
1000	10	Serpentine	Unidirectional	(28.9363, 28.9940)	(28.7466, 28.7992)	(91.6399, 91.7332)
1000	8	Perimeter	Cyclical	(28.6421, 28.7158)	(49.7593, 51.2827)	(66.8361, 66.9178)
1000	8	Perimeter	Unidirectional	(28.4704, 28.5440)	(49.5875, 51.1109)	(53.1606, 53.2256)
1000	8	Serpentine	Cyclical	(29.0664, 29.1374)	(50.1670, 51.7230)	(100.799, 100.923)
1000	8	Serpentine	Unidirectional	(28.9480, 29.0190)	(50.0487, 51.6047)	(91.3964, 91.5079)
2000	12	Perimeter	Cyclical	(28.3198, 28.3723)	(177.796, 179.781)	(68.0189, 68.0698)
2000	12	Perimeter	Unidirectional	(28.1518, 28.2043)	(177.628, 179.613)	(54.4043, 54.4450)
2000	12	Serpentine	Cyclical	(28.7540, 28.8045)	(178.151, 180.127)	(102.612, 102.689)
2000	12	Serpentine	Unidirectional	(28.6449, 28.6954)	(178.042, 180.018)	(93.7845, 93.8547)
2000	10	Perimeter	Cyclical	(28.2247, 28.2717)	(233.749, 235.829)	(67.5656, 67.6251)
2000	10	Perimeter	Unidirectional	(28.0598, 28.1068)	(233.584, 235.664)	(54.2933, 54.3411)
2000	10	Serpentine	Cyclical	(28.6564, 28.7010)	(234.108, 236.120)	(101.919, 102.008)
2000	10	Serpentine	Unidirectional	(28.5064, 28.5510)	(233.958, 235.970)	(89.8610, 89.9399)
2000	8	Perimeter	Cyclical	(28.3756, 28.4228)	(304.850, 306.894)	(66.9108, 66.9773)
2000	8	Perimeter	Unidirectional	(28.2024, 28.2496)	(304.676, 306.721)	(53.1062, 53.1590)
2000	8	Serpentine	Cyclical	(28.7981, 28.8481)	(305.192, 307.340)	(100.911, 101.012)
2000	8	Serpentine	Unidirectional	(28.6609, 28.7108)	(305.055, 307.203)	(89.9909, 90.0808)

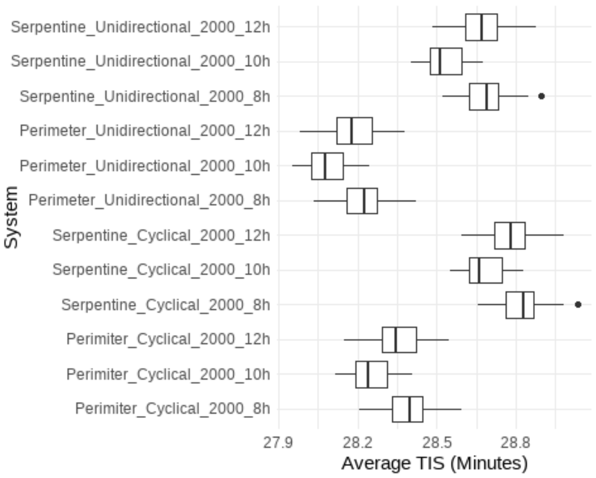


Figure 4: Average patient time-in-system by system settings assuming 2000 patient turnouts.

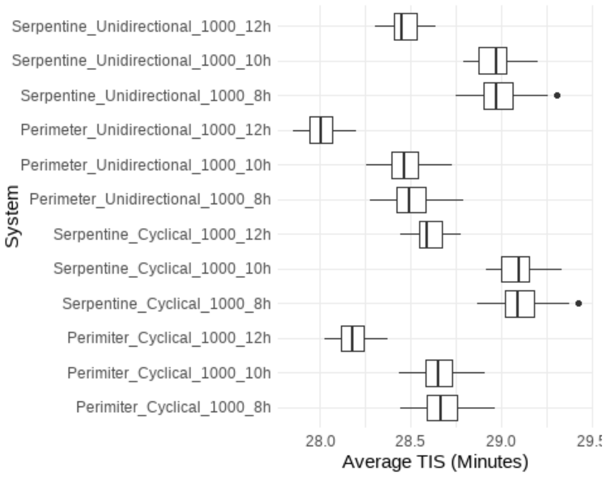


Figure 5: Average patient time-in-system by system settings assuming 1000 patient turnouts.

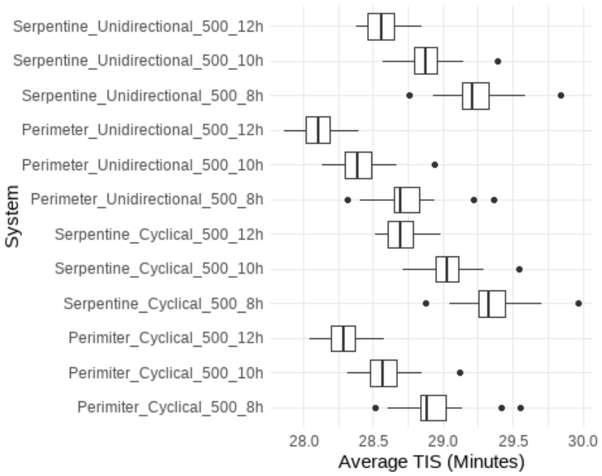


Figure 6: Average patient time-in-system by system settings assuming 500 patient turnouts.

Table 6: Differences in average TIS with optimal staffing by layout method (Minutes).

Turnout	System Settings	Layout method comparisons (Perimeter and Serpentine) for three clinic operational hours		
No. of Patients	Path	8 hours	10 hours	12 hours
500	Cyclical	0.4353***	0.4401***	0.4073***
500	Unidirectional	0.5105***	0.4698***	0.4468***
1000	Cyclical	0.4195***	0.4265***	0.4242***
1000	Unidirectional	0.4730***	0.4850***	0.4576***
2000	Cyclical	0.4248***	0.4282***	0.4378***
2000	Unidirectional	0.4608***	0.4430***	0.4968***

Note. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, na = not statistically different

Table 7: Differences in average TIS by path directionality (Minutes).

Turnout	System Settings	Path directionality comparisons (Unidirectional and Cyclical) for three clinic operational hours		
No. of Patients	Layout Method	8 hours	10 hours	12 hours
500	Perimeter Layout	0.1936	0.1797	0.1798
500	Serpentine Layout	0.1184	0.1500	0.1403
1000	Perimeter Layout	0.1718	0.1852	0.1737
1000	Serpentine Layout	0.1183	0.1267	0.1403
2000	Perimeter Layout	0.1733	0.1648	0.1680
2000	Serpentine Layout	0.1373	0.1500	0.1090

Note. Significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, na = not statistically different

4 DISCUSSION

DES was proven to be a valuable tool in analyzing the effect physical characteristics and equipment layout on the vaccine clinic system performance. To address research questions 1 and 2, this study found that average time-in-system for optimal staffing differed significantly between layout methods, while found no significant difference between layout methods with noticeable rise in TIS when keep 3, 6, and 12 servers at all turnouts for appointment check, clinical check, and vaccination stations, respectively. The average patient's travel distance is significantly different in comparison to layout methods for all clinic sizes. Path directionality was not found to be significant on the average TIS and TD for all systems. Therefore, the path routings or the number of separate entrances and exits does not alone significantly affect the average TIS and TD. The average patient travel distance was shown to differ significantly by layout method, however, the confidence intervals on the average total patient TD were relatively narrow due to the defined paths that the patient could take. The randomness in the patients' selection of vaccination station was the only variation in path length. As the optimal numbers of staffing for each clinic size are different for each system, the CI for average time-in-system is relatively narrow.

To address the research question 3, the findings demonstrate that the Perimeter layout method with Unidirectional path routing is associated with greater efficiency compared to the Serpentine Layout method and Cyclical path routing, as evidenced by lower values of travel distance and time-in-system. Also, as the number of patients attending the clinic increased, there was a noticeable rise in the average time-in-system (TIS) for the constant staffing configuration. This observation suggests that there was an imbalance between the availability of staff and the demand for services. The increase in patient turnout put pressure on the system, resulting in longer waiting times and potentially slower processing of patients. The findings highlight the need for careful staffing considerations to ensure a balanced supply and demand, particularly during periods of high patient turnout, in order to maintain optimal efficiency and minimize waiting times in the clinic.

Based on the Results, it is evident that the confidence intervals for the mean travel distance (TD) of all systems do not overlap. This indicates that there are significant differences in TD among the analyzed systems, given optimal staffing. Notably, the normalized travel distances allow for a consistent comparison of the average TD for each patient. The findings suggest that the number of patients and clinic operational hours do not have a statistically significant influence on patient travel distance. These results imply that factors other than patient turnout and clinic duration may play a more significant role in determining the travel distance experienced by patients within the clinic setting. Further investigation into these factors could provide valuable insights for optimizing patient flow and minimizing travel distance in vaccination clinics.

Future investigations can focus on designing clinics that are resilient for both patients and providers. This involves considering not only the optimization of travel distance for patients but also taking into account the fatigue experienced by healthcare providers. Particularly in the context of COVID-19, where the scarcity of healthcare providers posed a significant challenge, designing layouts that reduce the risk of disease transmission and minimize fatigue becomes crucial. Exploring strategies to create layouts that prioritize the well-being and safety of providers, while still minimizing travel distance and time in system, can contribute to more sustainable and efficient clinic designs. By addressing these research questions, we can strive to create clinic layouts that are not only patient-centric but also provider-friendly, promoting a resilient healthcare environment that balances the needs of both patients and providers.

5 CONCLUSION

The findings of this study demonstrate the significant impact of layout method on the performance of mass vaccination clinics given optimal staffing. The Perimeter layout with Unidirectional path routing was found to be more efficient in terms of average patient travel distance and average patient time-in-system compared to the Serpentine layout. Path directionality did not have a significant effect on TD and TIS for any of the layout methods at any turnouts. The patient turnouts and clinic operational hours did not exert a statistically significant influence on patient travel distance. No significant layout differences were found under constant staffing, but higher patient turnout increased TIS, indicating supply-demand imbalance. These findings highlight the importance of thoughtful layout design in optimizing the performance of vaccination clinics and provide valuable insights for the development of efficient and effective vaccination systems.

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