Simulation Model to Optimize Hospital Pharmacy Operation using Queuing Theory

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Abstract:
The pharmacy sector is a vital component in the ever-changing landscape of the healthcare business, with increased demands with high percentage of ageing population and the initiation of manufacturing and import of specialised medications. The efficient management of pharmacy operations is paramount to meet patients' rising expectations for swift, accurate, and safe medication services. This research explores the use of queuing theory, a mathematical framework for analysing waiting lines and service systems, in the pharmaceutical industry. It dives into how queuing models are used, their influence on operations, and their future possibilities. The results suggested that application of queuing theory can enhance the operation efficiency and could minimize the operational challenges. As pharmacies adjust to changing patient requirements and technology improvements, the application of queuing theory becomes more important, promising improved patient care and operational efficiency.

Keywords: Pharmacy, healthcare, queuing theory, waiting lines.

1. Introduction

The pharmacy sector is a critical component of the healthcare industry, responsible for ensuring that patients receive the right medications and healthcare advice through pharmacist (Hepler, 2004). In recent years, the demand for pharmacy services has surged due to factors such as an ageing population, increased access to healthcare, and the emergence of specialty pharmaceuticals (Yeganeh, 2019). This growth in demand has underscored the need for efficient and effective management of pharmacy operations to meet patient expectations and ensure the safe and timely delivery of medications (Curtiss et al., 2004; Yeganeh, 2019). The philosophy of pharmacy is to provide pharmaceutical care to the patients by pharmacist who is the responsible to suggest adequate drug therapy for the purpose of achieving definite outcomes that improve a patient's quality of life (Mohiuddin, 2020). This define the importance of precision in the delivery of adequate drugs to maintain the pharmacy quality services that contribute to meeting customer expectations for effective drug management. The adaptation of efficient pharmacy services is driven by the need to address several key challenges faced by pharmacies which includes patient expectations, medication safety and resource allocation. Patients expect swift and efficient service, often in a retail-like environment, making efficient queuing and minimizing waiting times crucial for customer satisfaction while ensuring the accuracy of prescriptions and preventing medication errors is paramount in the pharmacy sector (Mittal and Sharma, 2022). Managing workflows effectively can reduce the risk of errors.

Pharmacies must strike a balance between staffing levels, inventory management, and customer demand, especially when dealing with fluctuations in patient volumes (Latif, 2018).

Queuing theory, a mathematical and analytical framework that studies waiting lines and the management of service systems, has found a burgeoning application within the pharmacy sector (Obamiro, 2010). The use of queuing models in pharmacy operations is becoming increasingly significant, helping pharmacies enhance customer service, optimize resource allocation, and streamline their workflows (Alowad et al., 2021). The application of queuing models in healthcare is not new; it has been an established practice for optimizing service operations in various healthcare settings, including hospitals and clinics. However, the unique demands and complexities of the pharmacy sector have given rise to a growing interest in the adaptation of queuing models specifically to pharmacy workflows. The application of queuing theory identifies the various dimensions of queuing models in the pharmacy sector, shedding light on how these models are applied, their impact, and the potential for future development (Brandenburg et al., 2014; Yaduvanshi et al., 2019; Fares and Amir, 2021).

2. Literature Review

Queuing models hold immense promise for addressing the critical issues faced by pharmacies, ultimately resulting in improved patient care and operational efficiency. By optimizing patient flow, minimizing waiting times, and enhancing resource allocation, these models have the potential to revolutionize the pharmacy sector. Gupta et al. (2009) conducted an extensive study on the application of queuing models for resource allocation in hospitals. They emphasized that effective resource allocation can lead to significant cost savings and, more importantly, can enhance the quality of patient care. By using queuing models, healthcare administrators can make data-driven decisions about staff scheduling, equipment allocation, and facility design to ensure that resources are efficiently utilized. van der Bahadori et al. (2014) conducted a study to determine the optimum operational characteristics of pharmacy situated within the hospital. The patients referred to pharmacy were categorised under different shifts and patients load were observed using queuing theory during the peak operational hours in each shift. The queue length for operational such as prescription filing and billing are the major departments that attracts the longest queue lengths and require further resource allocation. Ouderaa et al. (2016) explore the practical application of queuing models to minimize patient waiting times and enhance patient satisfaction in emergency healthcare settings. They stress the significance of real-time data analysis and decision support systems that incorporate queuing theory, enabling healthcare professionals to make dynamic adjustments to staffing and resource allocation. Feng et al. (2021) delve into the use of queuing models to improve scheduling and reduce patient waiting times in outpatient clinics. The authors emphasize the importance of patient-centered scheduling, which minimizes waiting times and improves patient experiences. By implementing queuing models, healthcare administrators can create efficient scheduling systems that consider both patient demand and clinic resources (Mittal and Sharma, 2020). Wu et al. (2020) explore how queuing models are used to optimize the delivery of healthcare services in patients' homes. This approach ensures that patients receive timely and appropriate care in the comfort of their residences. Queuing models play a crucial role in the efficient allocation of home healthcare resources, including staff and equipment. Kumar et al. (2023) addresses the role of queuing models in optimizing pandemic response operations. During

the pandemic, queuing models were used to ensure efficient patient flow, reduce wait times, and maintain social distancing. This helped healthcare facilities respond effectively to the crisis and ensured that testing and vaccination services were delivered with the utmost efficiency, ultimately contributing to the control of the pandemic.

The literature review suggested that, the application of queuing theory not only reduces the strain on emergency departments but also ensures that patients receive timely and appropriate care, which can be a matter of life or death in critical situations. Queuing models are valuable tools for optimizing customer service and resource allocation in retail pharmacies. Therefore, this study is aimed to provide a comprehensive understanding of how queuing models can be applied within the pharmacy sector, covering complete pharmacy settings, from retail and hospital pharmacies. The study highlights the benefits and challenges associated with implementing queuing models in pharmacies.

3. Material and Methodology
3.1. Study Area

A study has been carried out in a military hospital located of Delhi. The hospital has 40 departments, including clinical, financial, and administrative operations. The hospital also includes referral, teaching, specialised, and subspecialized facilities consisting 812 beds. The average annual occupancy rate of beds was found as 81 percent, and an average stay duration of patients was 4 days. The outpatient pharmacy located within the hospital was a specialist pharmacy, and the time of study considered for serving patients in two shifts: morning (8 a.m. to 12 p.m.) and evening (from 02 p.m. to 10 p.m.). Four employees worked in the morning shift (two for receiving, one for filling, and one for delivering prescriptions), while five worked the night hours (2 for receiving prescriptions, 1 for filling, and 2 for delivering prescriptions).

3.2. Methods

All patients referred to this hospital's outpatient pharmacy throughout its two morning and evening work periods. The total patient load received by the pharmacy is called as population in this study. The record of the 240 patients were investigated (120 patients in each shift), who visited the pharmacy in a weekday. The patients visited the pharmacy were handled on FCFS basis. The some of the patients enquire about availability of medicines, reneging of patients, unpaid or jockeying due to some emergency was not considered in the analysis. Only the patients attended the entire process of medication at every counter of pharmacy were considered for the analysis.

Patients who were sent to the hospital pharmacy were examined using this sample technique at regular 30-minute intervals from 8 a.m. to 10 p.m. (assessed by a chronometer). Using prepared paperwork, an observer recorded arrival times as well as the moments when the prescription was passed, filled, the cashier was consulted, the medicine was delivered, and the observer left.

The SPSS (Statistical Package for the Social Sciences) software, version 18, was used to evaluate the data that had been gathered (SPSS Inc, Chicago, IL). Using the analysed data, we calculated the arrival rate (λ)—the number of clients entering the pharmacy during the standard study time (30-minute intervals) and the rate of receiving services (μ), which is the duration of providing services to each patient every 30 minutes in this revised pharmacy queuing system—in order to analyse queuing theory variables. We computed the queuing network performance indicators for the hospital's

current pharmacy status in two work shifts under study based on these parameters. These indicators included the average number of patients receiving services, the average number of patients referred to the pharmacy, the average amount of time patients waited in line, the average amount of time patients spent in the pharmacy, the average amount of time patients was not immediately served after entering the pharmacy, and the system utilisation indicator.

ARENA software, version 12, was used to create a simulation model after the data collection and analysis for this updated investigation (Rockwell Softwares Corporation). After the queuing model was finished, we looked at four different situations. During this stage, we suggested operational solutions for enhancing the hospital outpatient pharmacy's queuing system using existing resources and maximising the service delivery mechanism, based on the study of queuing theory and the outputs of the pharmacy simulation model.

3.3. Study Variables

The study focuses on the following variables:

- Arrival Rate (λ) and Service Rate (μ) in the morning and evening shifts.

- Queue Lengths (Lq) and Patient Waiting Times (Wq) in both shifts.

- Scenario-specific changes in queue lengths and waiting times.

The patients arriving to the box as shown in figure 1 is the arrival rate and moving out per unit of time is service rate. The patient spend time in the box is the patient waiting time in queue.
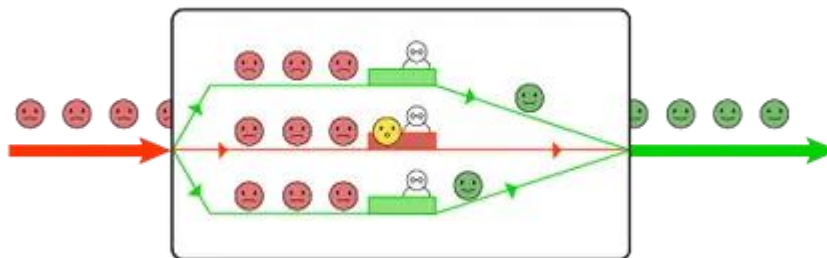

Figure 1: Markov chain M/M/1 queuing model

3.4. Queuing Network Performance Analysis

The queuing theory variables are assessed using the standard formulas:

- The average number of patients receiving services (ρ) = λ / μ.
- The average number of patients referred to the pharmacy (Ls).
- The number of patients referred to the pharmacy (Lq)
- The average waiting time in queues (Wq)
- The average total time spent in the pharmacy (Ws).
- The average time of not receiving immediate services after entering the pharmacy (Wa) = 30 / ($k\mu$ - λ).

- The utilization indicator of the system (ρ) using the formula $\rho = \lambda / k\mu$, where k is the number of servers available for the patients

Kendall's notation: M/M/1: FCFS/∞ used to develop and implement the queuing theory.

$$P_0 = \left\{1 + \frac{\lambda}{k\mu} + \sum_0^k \frac{\rho^n}{n!}\right\}^{-1}$$

$$L_q = \frac{P_0}{k!}\left(\frac{\lambda}{\mu}\right)^k \rho(1 + 2\rho + 3\rho^2)$$

$$L_s = L_q + \frac{\lambda}{\mu}$$

$$W_q = \frac{L_q}{\lambda}$$

$$W_s = W_q + \frac{30}{\mu}$$

All the variables are determined to assess the model performance and determine the adequate capacity of pharmacy to support the efficient delivery services without any delay and formation of long queues. The different scenarios were simulated involving different parameters to determine the evaluation matrix from the flow process of pharmacy, as shown in figure 2.
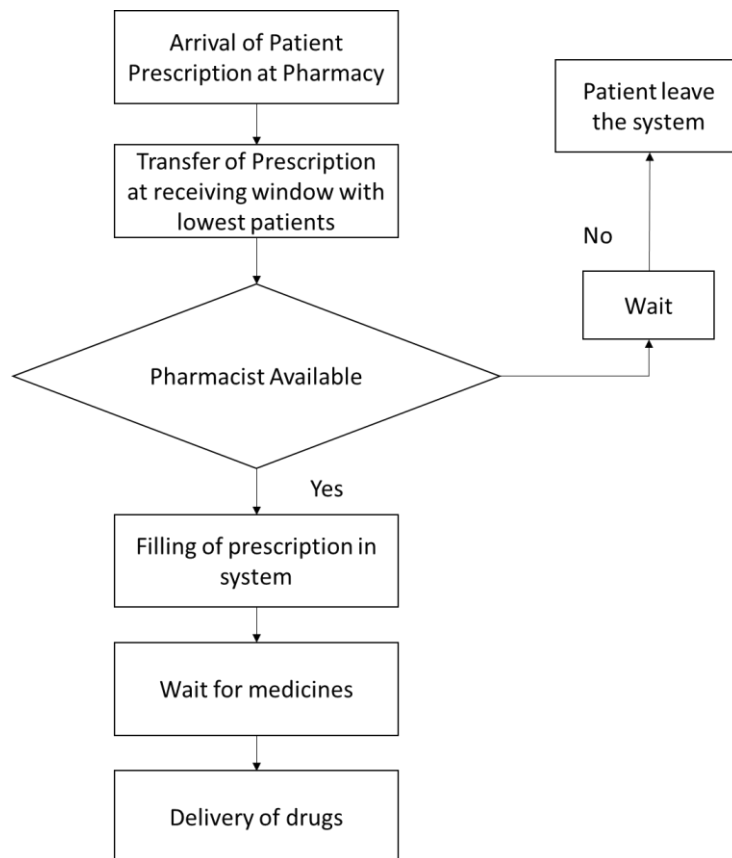

Figure 2: Flow process of operation cycle of pharmacy

4.   Results and Discussion

The total number of patients approaching the pharmacy is considered as infinite and was served on FCFS (First come First Serve) basis. All the patients are subjected to single server along with multi-phased operation for different type of activities. The total number of patients approaching the pharmacy follows the Poisson ratio whereas the delivery services follows the exponential curve as shown in Table 1. The flow of patients and service rate during both the shifts is shown in figure 3. The model simulation suggested that 24.8% of patients referred to the pharmacy in the morning shift and 28.5% of patients referred in the evening shift.

Table 1: Arrival and Service Rate in Pharmacy's Shifts

S.No	Pharmacy Shift	Arrival rate (λ)	Service Rate (μ)
1	Morning	26	24
2	Evening	30	27

The performance of the queuing model has been evaluated as shown in Table 2. The model suggested that average time in pharmacy for patients is 35.58 minutes in the morning shift and nearly remains same in the evening hours as 35.31 minutes. The average time spend by the patient in queue in the morning and evening shift is 34.33 and 34.20 minutes, respectively. The total queue length and distribution of number of patients in queue is simulated for both the shifts as shown in table 2. The simulation results suggested that evening hours receives the high percentage of patients (28.5%), whereas has lower waiting time in queue due to better service rate in the evening shift. The probability of queue length with zero patients in the queue for morning and evening shift is 0.338 and 0.329, respectively. Whereas, the probability of 5 patients in queue is 0.004 for both the morning and evening shift, as shown in figure 4. The prescription took the most time among all the activities and the average time invested by patient in prescription queue is nearly 24.4 minutes and more than 75% of patients faced the queue length more than 5 persons, whereas 62% of patients faced the queue length of more than 10 persons.

Table 2: The Queuing model performance in both shifts

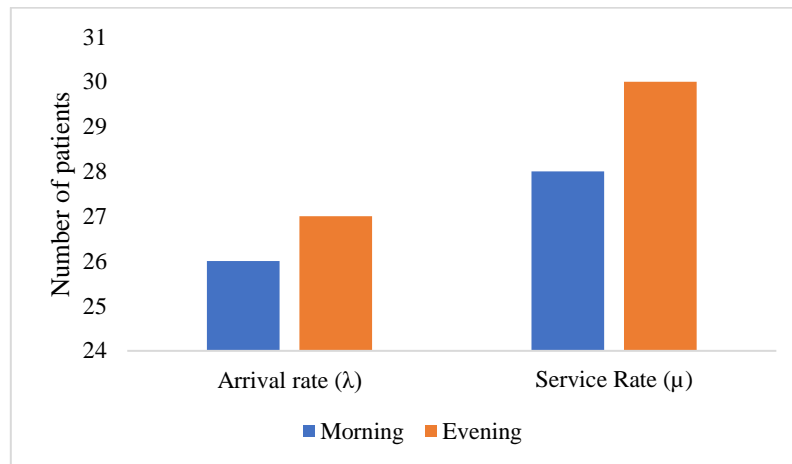| Variable	Morning	Evening
ρ	1.083 Persons	1.11 Persons
Ls	30.843 Persons	35.31 Persons
Lq	29.76	34.2
Ws	35.58 min	35.31 min
Wq	34.33 min	34.2 min

Figure 3: Patient arrival and service rate in hospital pharmacy

Table 3: Probability of customers in the Queue Length

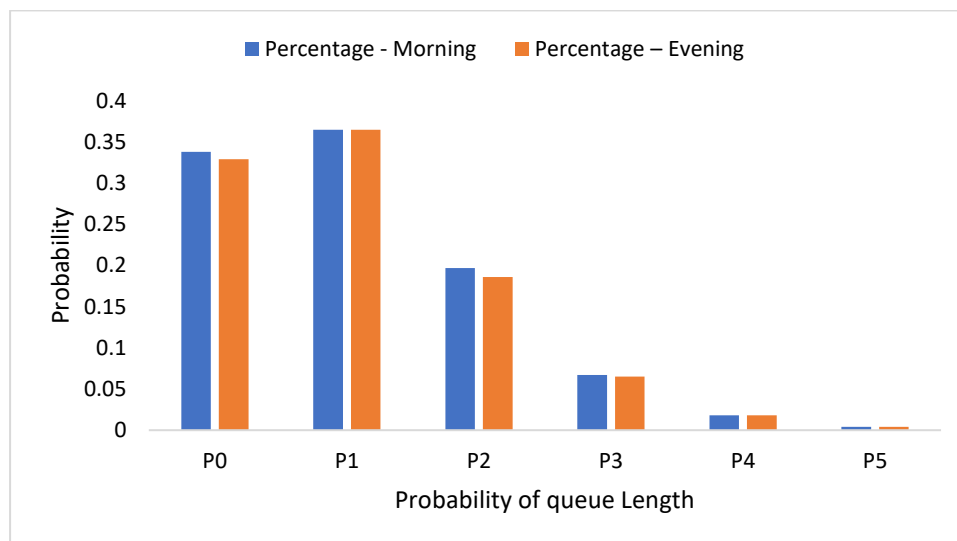| Probability	Percentage - Morning	Percentage – Evening
P0	0.338	0.329
P1	0.365	0.365
P2	0.197	0.186
P3	0.067	0.065
P4	0.018	0.018
P5	0.004	0.004

Figure 4: Probability of percentage of person in queue length

Table 3 suggest that longest time spend by the patients at the pharmacy occurs at the prescription filling stage during both the shifts. More than 60% of the patients spend time in queue of more than 10 patients while submitting and prescription filling stage. In order to resolve the issue of long queues at multiple windows, different plans were created to improvise the operational process and performance of each planned scenario is simulated for evaluation of best scenario. The four scenarios

were created to simulate the operational behaviour of pharmacy's operation while optimizing the available resources.

Scenario 1: Increase in employee performance by 25% receiving the prescription in the morning shift

Scenario 2: Increase in employees filling the prescription in the morning shift

Scenario 3: Combining the operation of receiving and delivering the drug in the evening shift

Scenario 4: Increase in employee filling prescription in the evening shift

Table 4: Queue length and waiting time under different scenarios

Variables		Average queue length (persons)	Average waiting time (mins)
Scenario 1	Before	2-3	2.25
	After	1-2	1.38
Scenario 2	Before	>12	24.4
	After	<2	6.16
Scenario 3	Before	1-2	1.43
	After	1-2	2.05
Scenario 4	Before	>7	20.02
	After	<3	8.15

In the first scenario, the service delivery at the prescription filling counter was i by 1ncreased by 25% and found that waiting time in the queue is reduced from 135 seconds to 83 seconds. The service delivery is the prominent area requires improvisation to handle the long queue length. It has been identified that moderate variation in method of receiving the prescription could improvise the operation and reduce the queue length. In another scenario, the one person increased at the prescription filling stage and found that queue length has been reduced to less than 20% of actual length. The time spend in queue by patients reduced to 6.16 minutes from 24 minutes. The drug delivery isn't the busiest section in the pharmacy and found in another scenario that reduction in 1 person in drug delivery shall not generate the significant difference in the performance of pharmacy. Where waiting time is expected to be increased by 30 seconds by combining the operation of delivery of drug and receiving of prescription. Both the operations could be handled by the same person with the marginal increase in operation time. The study also reflects that employing multitasking personnel in the pharmacy could change queuing model and improve patients' queuing status. Comparing the scenario 2 and 3, no new manpower is required to be hired in pharmacy, instead to that one person can be transferred in-between prescription filling and drug delivery services as per requirements. Whereas, scenario 4 was also found supporting the finding of scenario 2, which suggested the reduction in queue length by increasing the manpower at prescription filling point of service as shown in figure 5. The increase in one person could reduce the queue time from 20.02 minutes to 8.15 minutes and more than 50% of time can be saved under this scenario. The findings suggested that single server models generate the long queues due to single point of services, whereas conversion of single server to multiple server can reduce the length of queues and can minimize the waiting time.
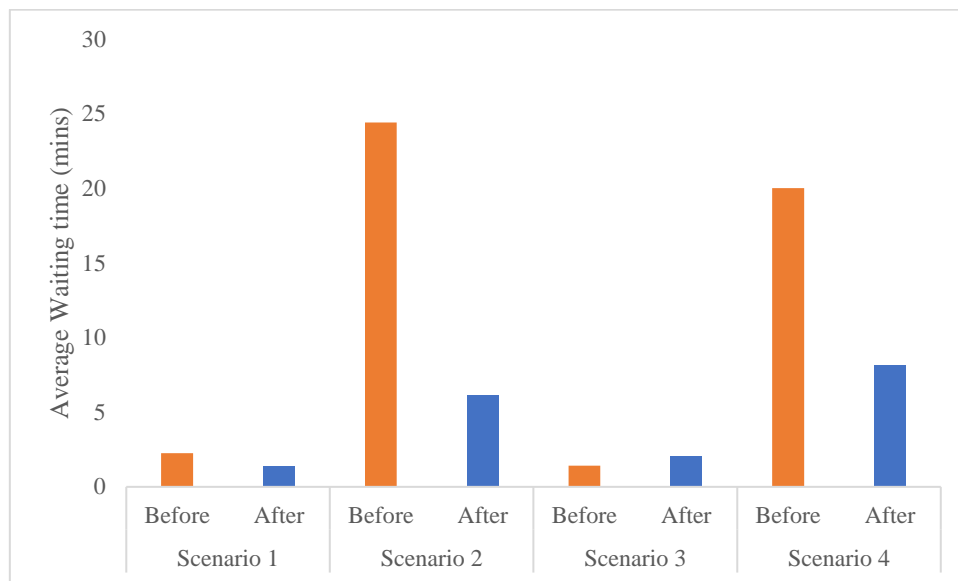
Figure 5: Average waiting time in minutes under different scenarios

The scenarios presented in Tables 4 provide insights into the repercussions of changes in personnel and procedures on queue lengths and waiting times. The data demonstrates that reducing the number of prescription receivers in the morning shift leads to increased average queue lengths and patient waiting times. Conversely, increasing prescription filling personnel in the morning shift results in a substantial reduction in queue length and waiting times. These scenarios underscore the pivotal role of staffing levels in optimizing the pharmacy's efficiency. Furthermore, the research evaluates the impacts of reducing the number of drug delivery personnel in the evening shift and increasing prescription filling personnel in the evening shift. The findings reveal that a reduction in drug delivery personnel results in a slight increase in queue length and patient waiting times. However, increasing prescription filling personnel in the evening shift leads to a notable decrease in both queue length and waiting times. This highlights the critical importance of appropriate staffing during the evening shift to ensure efficient service.

5. Conclusion

The presented research offers valuable insights into the performance of a pharmacy's work shifts, with a specific focus on queuing network indicators and the consequences of different operational scenarios on patient waiting times and queue lengths. This discussion summarizes the key findings and implications of the study, shedding light on the dynamics of pharmacy operations.

Central to this research are the queuing network performance indicators which are fundamental in assessing the efficiency and effectiveness of the pharmacy's operations. The results show that during both morning and evening shifts, the average number of patients receiving services (r) is approximately 1. This suggests a balanced system where the pace of patient service matches the rate of arrival, indicative of effective operations. However, the study uncovers variations in queue length and waiting times experienced by patients, underscoring their significant impact on overall satisfaction and the pharmacy's efficiency.

Analysis of queue lengths during the morning shift reveals that a majority of patients (approximately 55.8%) face queue lengths of 0-5 people, a positive aspect in minimizing wait times. In contrast, the evening shift exhibits a different distribution, with about 30.8% of patients facing queue lengths of 15-20 people. This disparity may be attributed to various factors, including staffing levels and patient flow patterns during different shifts. It is evident that staffing levels and shift-specific management are significant drivers of pharmacy performance. Proper alignment of personnel with patient demand is essential to minimize queue lengths and waiting times, thereby enhancing patient satisfaction and operational efficiency. The results underscore the need for proactive management and staffing adjustments to address fluctuations in patient arrivals effectively.

In conclusion, this study underscores the importance of queuing network analysis and the evaluation of diverse scenarios in optimizing the performance of pharmacy work shifts. The research highlights the significance of aligning staffing levels with patient demand and the potential for substantial enhancements in service quality and efficiency. Future research could explore the implementation of real-time data and advanced queuing models to further enhance decision-making processes in healthcare settings. These findings provide a valuable foundation for enhancing the efficiency and quality of services provided by pharmacies in various settings.

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