A GENERIC MODELING APPROACH TOWARDS SIMULATING AN URBAN PRIMARY AND SECONDARY HEALTHCARE FACILITY NETWORK

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ABSTRACT

We present a discrete-event simulation model of patient flow operations across public primary and secondary healthcare facilities in an Indian urban district. We made in-person visits to dispensaries, primary urban health centers (PUHCs), and polyclinics to collect operational information regarding service times, patient arrival rates, and medical resource capacities. We estimated probability distributions of the service times of healthcare providers using goodness-of-fit tests. We used a generic modeling approach to develop simulation models for each facility type and later integrated them into a network simulation. We evaluated operational metrics including average resource occupancies, average waiting time, and lengths-of-stay estimates in real-time across the network. We investigated how services would be provided to patients by varying capacities of resources experiencing bottlenecks in the network. Our hierarchical and multi-service network simulation is reusable that can be adapted via a network generic modeling approach to other similar facilities in the Indian and International context.

Keywords: primary and secondary healthcare, hierarchical healthcare delivery network, discrete-event simulation, generic modeling.

1 INTRODUCTION

Healthcare facilities aim to find ways to provide affordable and quality care to patients (Kucukyazici et al. 2020). The scarcity of medical experts and specialized equipment, rising healthcare demands partly due to the aging population, increasing cases of acute and chronic illnesses, and unnecessary medical visits, preferences for seeking care from private providers are a few significant challenges faced by healthcare administrators around the world (Schoenfelder et al. 2020). Accessibility, timeliness, universal healthcare coverage, and affordability form the key aspects expected from public healthcare delivery systems. Keskinocak and Savva (2020), Ansah et al. (2021) among many others demonstrated the utility of implementing operational research methods such as simulation modeling, analytical techniques, and simulation-based optimisation to help healthcare administrators improve the healthcare delivery to the target population. Simulation modeling evaluated the performances of existing healthcare systems and assessed the impact of potential changes in the healthcare delivery systems in a risk-free environment without considering the time and costs associated with experiments conducted in real-world settings (Elalouf and Wachtel 2021). In the current work, we demonstrated the use of the generic modeling (GM) approach in developing a network simulation model of public primary and secondary healthcare facilities in South-west Delhi, a large Indian urban district.

Delhi has a hierarchical healthcare delivery system with dispensaries and PUHCs at the primary level and polyclinics at the secondary level. Tertiary care is usually provided in district hospitals and highly specialized units for severe conditions. Based on in-person visits to facilities at the primary and secondary levels that differed in terms of the severity of illnesses being treated, we observed significant variations in the availability of medical resources, patient loads, and the provision of medical services leading to overcrowding at few facilities. In this context, modeling and analyzing flows of patients visiting these facilities becomes important to guide healthcare administrators on how to streamline healthcare delivery operations. Hence, as part of this, we recorded operational details on average patient loads, availability of medical care providers such as doctors, and staff nurses, consultation time of these providers, and mapped patient flows at these facilities. We categorized similar-level healthcare facilities into multiple types based on common operation details. We used the GM approach in conjunction with discrete-event simulation (DES) to develop a simulation model of each facility type at the primary and secondary level, reconfigured it to develop models of other types, and combined these to develop the healthcare facility network of the entire region. We adopted the GM approach owing to the existence of multiple instances of dispensaries, PUHCs, and polyclinics encountered during in-person visits. GM approach allowed the flexibility to model a wide variety of operational configurations of the healthcare facilities with minimal effort. Network simulation outcomes indicated a significantly higher utilization level of medical resources of the polyclinics compared to other facilities, also encountered during in-person visits. We evaluated the effect of changes in operational patterns on patients' lengths-of-stay (LOS) and utilization levels of the stressed resources.

We provide an overview of the relevant literature in Section 2. We present the background information about the healthcare facilities and the steps involved in developing a network simulation model using the GM approach in Section 3. In the penultimate section, we present the network simulation and the sensitivity analysis results. We make concluding remarks and discuss future avenues in the last section.

2 LITERATURE REVIEW

We focus the review on the implementation of operations research (OR) techniques for evaluating the performances of service systems. We discuss the application of simulation techniques to model patient flow operations and the use of GM approaches in health simulations in the International and Indian context.

2.1 OR Methods Review

Negahban and Smith (2014), Rondini et al. (2017), and others discussed the application of simulation and optimization techniques for analyzing complex operational problems in transportation, manufacturing, healthcare, and other industries. Optimization models mostly relied on closed-form mathematical formulations, hence were unsuitable to model intricate operational details without introducing simplifying assumptions such as stationary arrival and service processes, state-independent service processes, simplified priority rules, etc. observed at the healthcare facilities. Simulation techniques offered insignificant flexibility in modeling complex systems by incorporating stochasticity and uncertainties to allow stakeholders to develop and evaluate the impact of potential changes in healthcare deliveries (Salmon et al. 2018).

Simulation methods were categorized into four main groups: Monte Carlo, DES, system dynamics (SD), agent-based modeling, and more recently hybrid techniques (Friesen and McLeod 2014, Nguyen, Megiddo, and Howick 2022). Each simulation technique had its advantages concerning specific aspects of healthcare such as individual patient characteristics, and time-dependent and stochastic characteristics to make models capable to approximate real-life behaviors. DES was commonly used in medical facilities while SD was useful in epidemic modeling and disease prevention efforts. We refer readers to Katsaliaki and Mustafee (2011) for understanding extensive use of simulation in solving diverse healthcare problems.

2.2 Simulation Modeling at Healthcare Facilities

Lane and Husemann (2018), Nguen, Megiddo, and Howick (2020), Fatma and Ramamohan (2023), and others modeled a broad range of important problems faced in managing, designing, and delivering healthcare services ranging from modeling disease progression, identifying measures to reduce disease transmission, predicting newer cases, developing referral models for patients experiencing longer waiting times at the healthcare facilities. Previous studies modeled the micro-level movement of patient flows within a discrete service unit such as emergency departments, intensive care units, pediatric eye clinics (Tan, Goh, and Gunawan 2021), phlebotomy and specimen collection centers (Rohleder, Bischak, and Baskin 2007), psychiatric facilities (Long and Meadows 2018). Idigo et al. (2021) optimized scheduling strategies of patients in the radiology department of a tertiary hospital in Nigeria. Al Owad et al. (2018) measured the waiting time without describing how the service time distributions were estimated in the simulation model. Ashton et al. (2005) and Rohleder, Bischak, and Baskin (2007) focused only on estimating metrics around waiting time such as the number of patients in the waiting room, walk-in center patients with and without triage throughout a week.

In comparison to modeling of single units of healthcare facilities, a significantly lesser number of literature focused on simulation modeling and analysis of multi-service (Ashton et al. 2005, Ortíz-Barrios et al. 2017) and hierarchical healthcare facilities (Brailsford et al. 2004, Mestre et al. 2012, Mohd et al. 2021). Ashton et al. (2005) presented a simulation model of a multi-service facility to guide managers on how to model patient flow through new health centers. In the Indian context, Rema and Sikdar (2021) applied the Monte Carlo simulation technique to analyze queueing patterns and estimated key performance indicators to enable the health administrators to manage patient flow to enhance service operational efficiencies at the outpatient department of a healthcare facility. Major reasons for not modeling the medical delivery operations of healthcare facility networks could be significant resource requirements including time, money, and difficulties in obtaining permission from the administration to conduct data collection required for building simulation models of hierarchical and multiservice facilities.

Aiming at model reusability, Boyle, Marshall, and Mackay (2022), Mohd et al. (2021), and Shoaib and Ramamohan (2022) utilized GM approaches to develop simulation models of healthcare facilities for performance evaluation. Fletcher and Worthington (2009) compared the characteristics of 'generic' and 'specific' models and their success in hospitals for emergency patients. Careful reuse of simulation models reduced modeling time and cost. Shoaib and Ramamohan (2022) demonstrated the utility of GM and model reuse approach for primary care centers that served multiple types of outpatients and inpatients in a rural district in India. They surveyed primary-level healthcare facilities in a rural district, categorised them into different operational configurations, and provided a detailed demonstration of the implementation of the GM approach to generate simulation models of these configurations.

A significant proportion of the extant literature used DES to study a wide range of complex and dynamic healthcare problems at single units of the healthcare facility with most of the focus on inpatients and emergency care. A majority of them did not clearly report how the operational data were collected, which statistical tools were used to estimate the probability distributions of the input parameters, and how the input parameterization was done, thereby raising concerns regarding the reliability of the results. Further, a very small number of studies focused on modeling integrated facility networks at a hierarchical level catering to multiple patient types with distinct clinical and operational flows through the facility. Mohd et al. (2021) developed a network simulation model of a rural Indian public healthcare system. Compared to this work, we present a network simulation model of the urban public primary and secondary healthcare facilities offering larger variety of medical services. Further, Mohd et al. (2021) took the majority of input parameters from previous studies, while we conducted a more comprehensive data collection effort. Our work combined with Mohd et al. (2021) provides a comprehensive set of simulation models of public healthcare facility networks developed using GM for analyzing performances of the hierarchical and multiservice facilities in other countries with similar healthcare delivery systems. We chose DES over other modeling techniques as DES models are more accurate with respect to event timings without relying on defined system cycle time like Markov models, thereby producing more accurate results. We summarize the contributions of the present work: (a) demonstrate how the GM approach can be combined with DES to develop a hierarchical and multiservice healthcare facility network, (b) clearer description of how the input parameters were recorded and estimated for each facility type with consideration of KPIs from the patients and the healthcare administrator perspectives, and (c) demonstration of the applicability of GM approach based network model through the implementation of a real case study at the Southwest Delhi district in India.

3 NETWORK SIMULATION MODEL DEVELOPMENT

We obtained permission to visit public healthcare facilities across the Southwest Delhi district in India from the Directorate General of Health Services, Delhi. We surveyed a set of twenty-two public and primary healthcare facilities (out of 31 total) to observe patient flows and record operational data regarding the availability of medical resources such as general physicians (GPs), specialists, staff nurses, and other healthcare providers and the time spent by each of these providers on patients and the arrival rates at different departments of the healthcare facilities. We visited 17 dispensaries, 2 PUHCs, and 3 polyclinics to develop the network simulation model. We were unable to visit all facilities due to logistic restrictions.

Dispensaries attend to the patients requiring: (a) general outpatient department (OPD) care, (b) ante-natal care (ANC), and (c) vaccination and post-natal care (PNC). Dispensaries have one to two GPs for attending to general OPD patients, one receptionist for registering patient's details, one to two auxiliary nurses and midwives (ANMs) for attending to the ANC and vaccination patients, one pharmacist, and a lab technician. ANMs also provide PNC services to the mothers accompanying children for vaccination. We observed the patient flows and the provision of medical services at PUHCs to be similar to that of dispensaries. A few PUHCs also provide gynecologist consultation services to patients. In addition to providing general OPD consultation, ANC, vaccination, and PNC services, polyclinics also provide OPD-based specialist services to visiting patients on selected days of the week. The general OPD operates all six days a week while ANC and vaccination services are provided alternatively at these facilities.

We briefly describe the GM approach and the model reuse in the context of the public primary and secondary healthcare network simulation below. GM involves developing an archetypal model after surveying multiple healthcare facilities. The archetypal model represents the operational aspects common to all or most of the surveyed facilities which are modified and reused to represent the operations of other health facilities. Based on the operational details (patient flows, resource and staffing level and service time, etc.) collected during in-person visits from the surveyed facilities, we observed and identified commonalities and differences across the healthcare facilities of a similar type to broadly capture essential characteristics of the health facilities. We categorized the similar-level surveyed facilities into multiple types on basis of these commonalities and deviations such as the availability of one/two GPs and ANMs (staffing levels), provision of ANC, vaccination, and PNC services, and the delivery of specialised medical services at the facilities.

3.1 Patient Flow

We now briefly describe the flow of patients seeking medical care from dispensaries, PUHCs, and polyclinics. Based on our visits, we observed general OPD care was offered by all facility types, while only

Table 1: Operational Configuration Characteristics of Healthcare Facilities. *(GPs/lab technicians/pharmacist/receptionist/ANMs).

Health facility	**Dispensaries**			**PUHCs**		**Polyclinics**	
	Type 1* 2/1/1/1/2	**Type 2** 1/1/1/1/1	**Type 3** 1/1/1/1/0	**Type 1** 2/1/1/1/2	**Type 2** 1/1/1/1/1	**Type 1** 2/1/1/1/2	**Type 2** 1/1/1/1/2
General OPD	100-200	50-120	100-120	140-150	80-120	200-220	140-190
Gynaecology	NA	NA	NA	60-70	NA	60-70	20-50
Ophthalmology	NA	NA	NA	NA	NA	60-80	60-90
Orthopedics	NA	NA	NA	NA	NA	100-110	80-150
Pediatrics	NA	NA	NA	NA	NA	70-80	50-100
Dermatology	NA	NA	NA	NA	NA	120-130	NA
ENT	NA	NA	NA	NA	NA	80-85	70-90
Surgery	NA	NA	NA	NA	NA	40-45	15-45
ANC	40-50	15-40	NA	50-60	40-50	50-60	40-60
Immunization	45-55	20-40	NA	60-70	50-60	60-70	40-70

polyclinics offered OPD-based specialist services to patients. We rename general OPD patient flows as non-specialist flows. We present the non-specialist patient flow observed at the dispensaries, PUHCs, and the polyclinics, and the specialist flow observed only at the polyclinics in Figures 1 and 2 respectively.

3.1.1 Non-specialist flow: Dispensary, PUHC, and Polyclinics

Patients with normal ailment conditions like cough, cold, fever, body pain, etc join the registration queue upon entering the facility. The receptionist records patients' details such as name, age, and address in the OPD attendance register, and a brief description of their medical condition. After getting a general OPD registration slip from the receptionist, patients join the OPD queue and wait for their turn until the GP becomes available if the GP is busy attending to other patients. Based on the illness condition, the GP prescribes medications to patients in the registration slip and also suggests routine laboratory investigations for approximately 50% of the patients. Patients requiring lab investigations visit the in-house laboratories where basic tests such as hemoglobin tests, blood pressure tests, etc are performed. These test reports are provided in very short duration to the patients. Patients reconsult the GP to show the diagnosis reports. Once consultation with the GP is over, all patients join the pharmacy queue to collect the medicines, ointments, or cough syrups. In cases of drug unavailability, patients wait for the medicines to be restocked and visit the other day. All patients exit via the pharmacy.

Additionally, a few (nearly 10%) revisit the GP in case of uneasiness, difficulty in understanding the suggested medications, or other issues that develops in the meantime. Patients visit empaneled laboratories linked with healthcare facilities to undergo tests unavailable at the facilities.

ANC services are provided to the expecting mothers for six months with one visit scheduled each month till the last trimester of childbirth delivery. Upon entering the healthcare facility, ANC patients directly consult the ANM or join the ANM registration queue in case of unavailability of ANM. The ANM first confirms the visit number of the patients. In the case of the first visit, the ANM records patients' personnel details in the ANC attendance register and issues an ANC card to the patients. The ANC card contains a schedule of the next visits, required laboratory investigations, and other information on medication supplements to be provided to the patients in subsequent visits. After the registration, the ANM measures patients' weight, blood pressure level, body temperature, and respiratory rate, and conducts basic tests such as hemoglobin, blood pressure, etc as per the DGHS guideline. ANM provides iron folic acid tablets and calcium supplements

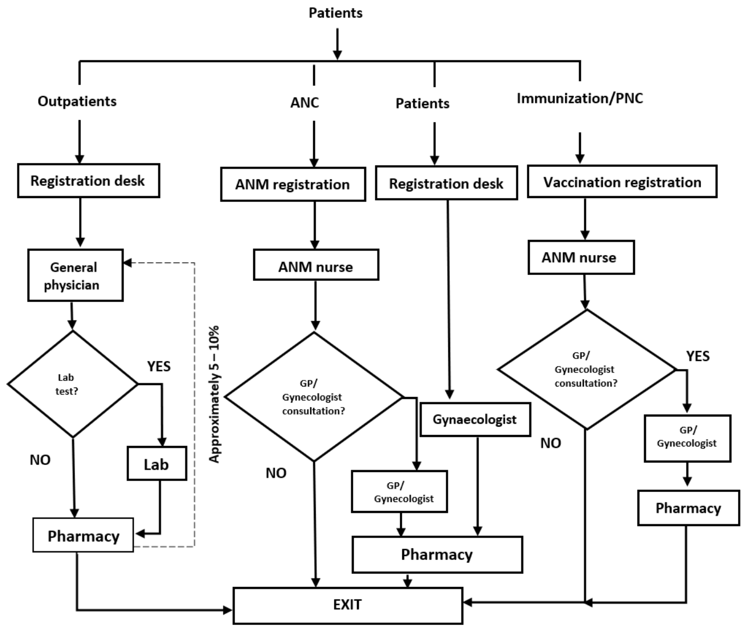

Figure 1: Patient Flow at dispensaries and PUHCs/non-specialist patient flow at the polyclinics. Note: Dispensaries has no gynaecologist.

of one month-dosage, immunisation injections (tetanus toxoid), diet-related consultations, nutritional and health counseling, and also confirms comorbidities such as tuberculosis, and diabetes from the patients. For patients with ANC cards, injections, and medications are provided as per the guidelines. The ANM further updates patients' card details in subsequent visits. The majority of the patients exit the facility after consulting the staff nurse. The ANM also suggests GP consultation to approximately 5 – 10% of the patients having high fever, or other medical concerns. ANM refers patients to GP for medical conditions beyond their expertise. All ANC patients are referred to the nearest Dadadev hospitals for childbirth delivery.

Routine immunization services are offered to children aged between 0 to 2 years. Along with this, PNC consultations are provided to accompanying mothers as recommended in the guidelines. There are in total six visits assigned to patients with four vaccinations scheduled during the first year i.e., at the end of the 2nd, 4th, 6th, and 12th month where the children are vaccinated against measles, chicken pox, hepatitis B, and influenza. Children are vaccinated against diphtheria, tetanus, whooping cough, and polio during the second year. Upon entering the facility, children join the vaccination nurse queue. Once their turn arrives, the ANM records patients' details, and measures the body weight and temperature of the patient. In case of the first visit, a vaccination card is made. ANM provides the required injections as per the schedule mentioned in the card and also measures the body temperature of mothers, counsels for family planning, and provides vitamin and calcium supplementation upon requirement. Patients exit after collecting the medicines from the facility. Owing to space limitations, we do not elaborate on the specialized flow observed at the polyclinics. The specialized patient flow shown in Figure 2 is self-explanatory.

3.2 Input Parameter Estimation

For estimating the distributions of the service time of medical resources they spent with the patients, we recorded the consultation time of multiple patients with GPs, specialists, receptionists, and others using a mobile phone stopwatch. The number of observations varied, for example, we collected seventy observations at the pharmacy counter and fifty observations at the receptionist counter of the dispensary. After

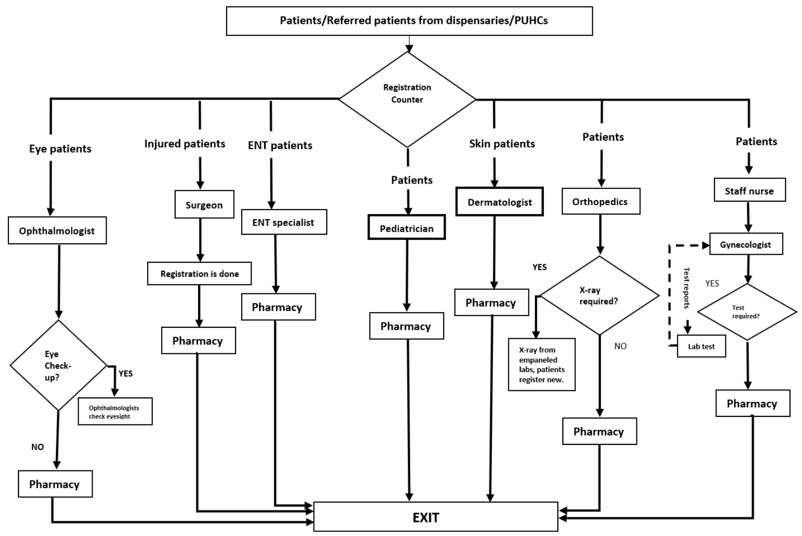

Figure 2: Specialist patient flow at the polyclinics.

recording the observations at multiple healthcare facilities, we first plotted box plots of these observations to remove the outliers. We imported the datasets into Minitab software and conducted the goodness-of-fit test to estimate the probability distribution of the service time. We used the Anderson Darling test score and the p-value estimate to determine the best-fit distribution as reported in Table 2. We found the best-fit distribution for the receptionist service time to be truncated Gaussian distribution with parameters N(0.57, 0.14^2) with a maximum and minimum service time of 0.25 and 0.93 minutes respectively. Due to space limitations, we do not provide the test statistics and the upper and lower limits of the service time that can be made available upon request.

Table 2: Service time estimates at the healthcare facilities. Note: Time estimates are in minutes.

Parameter	**Dispensary**	**PUHC**	**Polyclinic**
Reception counter	Lognormal(0.04, 0.38)	Normal(0.57, 0.14^2)	Lognormal(0.06, 0.39)
GP consultation time	Weibull(1.86, 1.64)	Normal (1.08, 0.33^2)	Lognormal(0.06, 0.53)
OPD lab technician time	Normal(3.09, 0.65^2)	Normal(3.35, 1.14^2)	Normal(3.09, 0.65^2)
ANC registration time	Gamma(5.28, 0.24)	Gamma(8.22, 0.45)	Normal(2.55, 0.81^2)
ANC injection time	Normal(3.87, 1.14^2)	Gamma(8.22, 0.45)	Normal(3.87, 1.14^2)
PNC registration time	Gamma(5.28, 0.24)	Normal(3.51, 1.12^2)	Gamma(5.28, 0.24)
PNC injection time	Normal(2.47, 0.73^2)	Normal(3.51, 1.12^2)	Normal(2.47, 0.73^2)
Pharmacy	Weibull(2.08, 2.41)	Gamma(5.39, 0.29)	Normal(1.86, 0.33^2)
Orthopedics	×	×	Lognormal(0.07, 0.49)
ENT	×	×	Normal(2.18, 0.56^2)
Pediatrics	×	×	Normal(3.93, 0.57^2)
Dermatology	×	×	Normal(2.38, 0.39^2)
Surgery	×	×	Normal(4.49, 0.69^2)
Gynaecology	×	Normal(2.55, 0.81^2)	Normal(3.88, 1.13^2)
Ophthalmology	×	×	Normal(2.93, 0.55^2)

To estimate the average interarrival time from each healthcare facility visited, we recorded the daily patient load from the attendance register and used these to calculate the mean interarrival time for patients visiting dispensaries, PUHCs, and polyclinics for a six-hour shift. We used exponential distribution for the interarrival time to model the patient arrival for all types. For Type 1 polyclinic, we assumed the interarrival time of 5 minutes as approximately 200 patients visit on a given day. Note that this is not a constant assumption. We followed a similar procedure to estimate the interarrival time at other departments of healthcare facilities. We did not consider follow-up cases owing to the new registration of each patient visiting these facilities. The parameter estimates reported in Table 2 are common across all dispensaries, PUHCs, and polyclinics.

Using the input parameter estimates reported in Tables 1 and 2, we developed an archetype DES model of healthcare delivery operations of Type 1 dispensaries, PUHCs, and polyclinics. We subsequently modified this archetypal model using the GM approach to develop DES models of Type 2 and Type 3 health facilities. After developing individual simulation models of seventeen dispensaries, two PUHCs, and three polyclinics, we integrated them to develop the public primary and secondary healthcare network.

4 NETWORK SIMULATION RESULTS

We developed the DES-based generic network model of the public primary and secondary healthcare facilities in Python language using *salabim*, an open-source Python-based DES package (van der Ham 2018). Salabim package supports animation, queues, states, monitors for data collection and presentation, and event tracing functionalities. We used global and local variables to store the input parameter estimates required for modeling the healthcare facility network simulation. We conducted the simulation experiments on a 64-bit operating system, 2.11 GHz, 16 gigabyte RAM workstation with an Intel(R) Core (TM) i7-processor. We ran the model for 180 days of warm-up time prior to collecting outcomes over a simulation time of 365 days. We report the key simulation outcomes including the occupancies of the medical resources, the average waiting time for each healthcare provider, and the average length of time spent by the patients at different departments of the healthcare facilities in different configurations in the network, generated from 40 replications in Tables 3 and 4 for patients seeking non-specialised and specialised services at the public

Table 3: Operational outcomes for non-specialist flows at public primary and secondary healthcare facilities. The number in parentheses represents the total number of facilities of each type. Note: ρ: average resource occupancy, w: average waiting time; *LOS*: average lengths-of-stay.

KPIs	**Dispensaries**			**PUHCs**		**Polyclinics**	
	Type 1 (7)	**Type 2 (9)**	**Type 3 (1)**	**Type 1 (1)**	**Type 2 (1)**	**Type 1 (2)**	**Type 2 (1)**
ρ_{GP}	29.72	50.27	53.25	22.95	36.37	24.91	41.63
ρ_{ANM}	58.44	44.37	NA	62.31	55.35	46.35	35.48
ρ_{gynae}	NA	NA	NA	53.07	NA	Table 4	Table 4
ρ_{lab}	57.12	48.35	52.38	62.19	49.03	62.79	52.49
$\rho_{pharmacy}$	80.80	68.39	72.42	77.68	102.71	130.24	103.08
$\rho_{receptionist}$	39.70	33.69	36.42	20.99	28.22	77.33	62.83
w_{OPD}	0.05	1.35	1.56	0.04	0.678	0.01	0.49
w_{ANM}	0.78	0.49	NA	1.34	0.80	0.64	0.70
w_{gynae}	NA	NA	NA	3.76	NA	2.33	1.76
w_{lab}	3.02	1.75	1.99	4.72	2.68	7.86	5.31
$w_{pharmacy}$	6.25	3.20	4.5	4.5	5.35	26.86	8.83
$w_{receptionist}$	1.27	1.10	1.17	1.01	0.75	1.55	0.83
LOS_{OPD}	15.53	13.03	14.26	12.67	13.66	30.22	17.70
LOS_{ANM}	6.23	5.94	NA	6.51	6.10	8.43	8.27
LOS_{PNC}	4.0	4.5	NA	6.76	6.11	7.10	6.92
LOS_{gynae}	NA	NA	NA	13.40	NA	51.22	23.41

primary and secondary healthcare facilities in the Southwest Delhi region.

We observed underutilization of the majority of the medical resources except for the pharmacist available at the polyclinics, with their utilization level exceeding 100% at Type 1 and Type 2 polyclinics. Further, the overall LOS of the outpatients was the highest at the polyclinics. The likely reason for this is that all polyclinics have a single pharmacy for the specialist and the non-specialist services, leading to a long waiting queue. This is also evident from the higher estimate of the $w_{pharmacy}$ (26.86 minutes) at Type 1 polyclinics. Consequently, the outpatients spend the majority of the time collecting the prescribed medications. Based on in-person visits, we also observed that pharmacists are closed after 2 PM irrespective of the waiting queue, and the patients are asked to visit the next day or after certain days in case of drug unavailability. The lower utilization levels of other medical resources such as GPs, specialists, ANMs, receptionists, etc, are likely due to the lower patient loads and low consultation time of the service providers. Based on operational outcomes reported in Table 4, we observed higher overall utilization of the specialists in the healthcare facility network. We report the mean time required to generate the results for each configuration and the entire network simulation model in Table 5.

Table 4: Operational outcomes for specialist flows at healthcare facilities. The estimates in the first and second row for each metric are from Type 1 and Type 2 polyclinics respectively.

KPIs	**Polyclinics**					
	Gynae	**Paediatrics**	**Ophthalmology**	**ENT**	**Dermatology**	**Surgeon**
ρ_1	41.32	61.95	56.01	41.35	45.34	86.33
ρ_2	31.23	46.77	50.53	37.77	NA	78.70
w_1	2.33	8.01	1.27	0.72	1.05	2.98
w_2	1.76	4.81	1.30	0.71	NA	2.63
LOS_1	51.22	55.20	49.56	48.57	48.82	52.66
LOS_2	23.41	25.07	18.58	17.43	NA	21.35

Table 5: Simulation run time (seconds).

Dispensaries			**PUHCs**		**Polyclinics**	
Type 1	**Type 2**	**Type 3**	**Type 1**	**Type 2**	**Type 1**	**Type 2**
208.57	159.89	56.17	253.62	239.65	289.80	277.84
Network	9630.99					

We also conducted sensitivity analyses to determine how polyclinics' operational outcomes respond to changes in the resource capacities of pharmacists. We performed this experiment as we observed significantly higher waiting times at the pharmacy queue of the polyclinics. We varied the average quantity of the pharmacist from the default estimate of 1 to 2. We present the results of these experiments in Figure 3. As expected, the LOS estimates for both specialist and non-specialist services reduced significantly with the increase in the capacity of pharmacists from one to two. For example, the average LOS estimates at the gynecology department reduce from 51.61 minutes to 14.01 minutes at the Type 1 polyclinic. We observed similar trends in other departments of polyclinics. We also observed that the pharmacist utilization reduced to 64.90% upon increasing the pharmacist capacity by 1. This indicates that having an additional pharmacist at polyclinics can be beneficial from the patient's and the health facility's perspective- lower LOS estimates for patients and lesser burden on the pharmacists for attending to the medical care needs of the patients.

5 CONCLUSION AND DISCUSSION

In this work, we used the GM approach in conjunction with DES to develop a network of public primary and secondary healthcare facilities in a large urban district. We visited multiple public primary and secondary

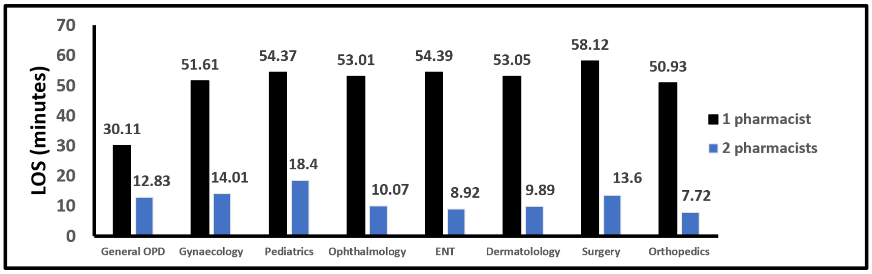

Figure 3: Effect of variation in the pharmacist capacity on patient LOS at the polyclinic.

healthcare facilities to collect operational data related to patient flow and staff and resourcing levels at these facilities. Owing to multiple instances of facility types encountered during in-person visits, we used the GM approach to develop the simulation models of the public healthcare facility network that can be modified and reconfigured to simulate the operations of hierarchical and multiservice public healthcare facilities in India and other developing countries. Our main purpose is to present the development and one example analysis that can be applied to different countries with hierarchical healthcare delivery system. In conjunction with Mohd et al. (2021), we provide a comprehensive set of DES based model that can be used to model other facilities. We developed the network simulation to evaluate the operations of the public healthcare system and analyze the effect of capacity reconfiguration on the operational outcomes of the healthcare network. Salmon et al. (2018) reported a significant number of previous studies utilized simulation modeling techniques to analyse the existing healthcare delivery system and evaluated benefits of implementing new service systems for the patients and healthcare providers. The hierarchical multi-service network simulation operational outcomes indicated higher utilization of the medical resources at the polyclinics in comparison to the lower-level healthcare facilities. This is likely because of the perception of a better quality of care at the higher-level healthcare facilities at the secondary level. Increasing the capacity of the pharmacists significantly reduced the overall LOS of the patients at the polyclinic. We observed the network simulation took one hundred and sixty minutes to generate the operational outcomes. We can discuss simplifications in the model with the healthcare providers to reduce this time further.

Generalization of our observations of the healthcare facilities across other districts of Delhi or other Indian healthcare facilities should be made with appropriate caution as we conducted visits to a single district only. Future avenues of the current work include the inclusion of district-level healthcare facilities in the current network of public primary and secondary healthcare facilities. This whole network in combination with another OR tool can be used to solve a number of operational problems being encountered by the patients, healthcare providers, and the healthcare administrators such as the integration of the traveling salesman problem within the network simulation to estimate and determine the optimal route for transferring patients to designated health centers in a pandemic situation. In this work, we did not validate the network simulation operational outcomes, however, based on our visits to multiple healthcare facilities, we consider the outcome to be nearly similar. In future work, we can validate the network simulation model using both internal and external validation techniques. For the internal validation, we can compare the average resource occupancies, average waiting times, or average LOS estimates to the corresponding analytical estimates obtained using queuing theory concepts. We can do external validation of the network simulation model by comparing its outcomes to the average wait time, LOS, or occupancy outcomes observed at the healthcare facilities at a 95% confidence interval using a t test. We can further include variations in the patient load at different times of the day, week, or season observed at these facilities in the network simulation model.

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