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Redesigning patient flow in paediatric eye clinic for pandemic using simulation

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Redesigning Patient Flow in Paediatric Eye Clinic For Pandemic Using Simulation

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***Abstract*—This study proposes a systematic approach to the construction of a simulation model to support decision-making concerning the capacity limit and staffing configurations at the paediatric eye clinic in Singapore under the COVID-19 pandemic situation. During the pandemic, the clinic must ensure that the operations are aligned to the safe-distancing regulations put in place by the Ministry of Health while coping with the demand. We developed simulation models to examine the 'as-is' process and proposed numerous 'to-be' processes for new clinic configurations to operate under the pandemic conditions. We combined scenario-thinking and simulation optimization to determine the additional manpower and physical resource requirements to enable the decision-makers at the clinic to better plan the necessary for continuous care to the young patients in a populated city, while coping with the healthcare demands during the pandemic.**

***Index Terms*—prescriptive analytics, simulation, healthcare, optimization, pandemic.**

I. Introduction

The Coronavirus Disease (COVID-19) is an infectious disease caused by newly discovered coronavirus that affected the livelihood of the world from December 2019. Singapore reported its first COVID-19 case on 23 January 2020 and started the 'circuit breaker' preventive measure on 7 April 2020 in response to the pandemic in the country. To prevent further spread, safe distancing was mandated by the Singapore Government. While essential workplaces remaining open during the circuit breaker period, all establishments must maintain at least one metre safe-distancing between individuals. Due to these measures, many establishments, including healthcare institutions were to implement restricted operations at a fraction of their usual operating capacity. The circuit breaker was lifted in early June 2020 with a three-phase transition plan by relaxing some measures.

In this paper, we define the scope of the study on the operations of a paediatric specialist eye clinic in Singapore. The clinic provides various tests, such as eye test, visual acuity test, and optometry services. Due to the circuit breaker and the safe-distancing measures during the pandemic, the number of appointments had been reduced significantly. After the circuit breaker was lifted, there was an urgency to clear the backlog of appointments. The objective of our study is to study the existing processes, patient load and available resources, to propose solutions to reconfigure the clinic under the new regulations to manage the demand while staying reactive to the pandemic situation and meeting the required service time, e.g., within thirty minutes of wait-time before being first seen by a doctor.

The process in this study involves dynamic and stochastic processes due to the uncertain nature of the patient arrival, the services required by each patient and the service times for each part of the process. We propose and build a simulation approach to derive prescriptive solutions to our problem. Our approach consists of three main parts, firstly to identify the bottleneck in the process in the clinic, then we used a data-driven method to identify the drivers that affects the average stay-time in the clinic and finally use simulation to predict and prescribe clinic configurations (e.g., number of service stations and staff required) for managing high demands in the populated city with resource restrictions, pandemic safe-distancing rules and hygiene guidelines from the Ministry of Health (MOH).

The main contribution of the paper is in its practical perspective where the models utilize empirical data from the real-world paediatric clinic with expert's validation and providing essential decision-making support to cater to the needs of the citizens in the city. The scientific contribution includes a systematic approach to abstract and model the complexity of patient's journey in the eye clinic under the restricted operating conditions due to the COVID-19 pandemic situation.

II. Literature Review

Discrete Event Simulation (DES) is defined as a simulation modelling that is intuitive and flexible [1], characterised by its ability to simulate dynamic behaviours of complex processes and interactions between individuals and their environments. Each process occurs at a particular simulated time and it marks a change of state in the system.

In the healthcare industry, DES is commonly used to comprehensively compare potential strategies and to identify the most efficient and practical recommendations to tweak the processes, especially in the clinic or operating theatre conditions. Furthermore, in comparison to other models such as system dynamics, DES is more applicable in modeling at an individual level, rather than at a cohort level [2], whereby entities such as the patients can be examined one by one as they wait in the queue [3].

The work in [4] presents the current advances and extend of DES applied in health care, which are classified into four major classes: health and care systems operation, disease progression modeling, screening modeling and health behavior modeling. Health and care systems operation covers more than 60% of number of publications, enabling health care managers to better understand the underlying mechanisms of how a system operates, comprehensively investigate the relationships among different sections with a system [5]. It covers six major operations research issues consisting of patient scheduling (e.g., appointment and discharge scheduling), resource allocation, capacity planning, staff scheduling, system diagnosis, and health economic evaluation.

Given that the context of this study, eye clinics are generally implemented on a smaller scale, unlike the emergency unit or operating theatre, DES is preferred for process simulation to allow examination on a detailed level and to capture the complexity and stochastic nature of the patient flows. The choice is aligned to the choice of simulation methodology that three existing studies on eye-related clinics had conducted. In [6], DES was used to examine scheduling and staffing policies for an Optometry Clinic with a goal of increasing the daily patient throughput. In [7], DES was used to reduced wait-time for Glaucoma patients. In Singapore context, the work in [8] used DES in Ophthalmic Specialist Outpatient Clinic in the Singapore National Eye Centre (SNEC) to design strategies for reducing the turnaround time for patients. Additionally, healthcare facilities in eye clinic have well-defined layout for reception, waiting area, consultation rooms, treatment rooms which is directly adaptable to model construction in a DES [9].

In relation to coping with pandemic conditions, recent works in the healthcare domain mainly involve use of simulation on predicting and managing overcrowding issues such as bed management [10] [11]. The literature in the Ophthalmology field such as [12] reports special care and hygiene practices in handling equipment and patients under a pandemic condition.

III. Problem Description

A. The Case Study

The case study in this paper focuses on the paediatric specialist eye clinic in Singapore. It operates on Monday to Friday from 7 am to 6 pm. The clinic handles new and chronic patients who are referred to specialist care by general practitioners. It provides eye test, visual acuity examination, and optometry services. In the past, while new patients are always provided an appointment, repeat patients may come in either by appointment or walk-in. Since the outbreak of the COVID-19 pandemic, patients could only visit the clinic strictly by appointments.

The process concerned is the outpatient flow. Typically, the patient (and his/her caregiver) enter the clinic and register via the registration desk. During the pandemic period, contact tracing procedures using SafeEntry application and additional health and travel declarations were added at the entrance and registration desks respectively. Next, the patient and caregiver will either be directly taken to Visual Acuity, Optometry, or to the reception area to wait for consultation. At the Visual Acuity, a simple vision assessment is performed. At the Optometry, more detailed assessment using optometry machine is performed. After the consultation, patients may be required to go for dilation where eye drops are administered or to go for further treatment at the Optometry. After the Optometry or Dilation activities, the patient may be required to re-enter the queue to consult with the doctor again. In most cases, the patients see the doctor at least once and up to three times during a visit. When all activities are completed, the patient will proceed to the payment counter to make payment. The process ends after payment.

The three common pathways taken by patients are depicted in Figure 1. The Type 1 patients require all services, Type 2 patients are usually the regular patients, so registration is not required. The Type 3 patients are the ones who visit the clinic for treatment and do not need to perform Visual Acuity and Dilation. The elongated circle in each activity in the diagram indicates the service time distribution while the number in the parenthesis indicates the maximum number of resources available to perform the activity. The arrow turning back to consultation shows the possible pathways that the patient may take, re-entering the main queue to consult the doctor multiple times. Three main types of resources supporting this process: the Service Staff, Optometrists, and the Doctors (i.e., Ophthalmologists).

B. Challenges

Since COVID-19 pandemic, the clinic has put in place additional safety measures, such as additional safe-distancing check-in counters before entering the clinic and setting lesser capacity due to safe-distancing directives. MOH has implemented SafeEntry, a smart city and national check-in system which enables the logging of visitors at various locations in Singapore for contact tracing purposes. The safety measures impose additional stress on the operational requirements on the clinic and affect process taken by the patients. In the past, patients were just required to proceed to the respective clinic and the capacity was much higher than during the pandemic.

C. Objectives

The objectives of this study is to evaluate the pre-pandemic ‘as-is’ process and investigate the ‘to-be’ physical configurations required for operating the clinic during the pandemic using discrete event simulation. The focus of the study is in health and care systems operation. We define the objectives of our study as follows:

1) To determine the operational requirements for Safety Checks at the entrance
2) To evaluate the number of patients that can be scheduled or served such that the clinic adheres to safe-distancing guidelines and the corresponding system behaviours (e.g., average system wait-time, stay-time and throughput) are within the desired targets.

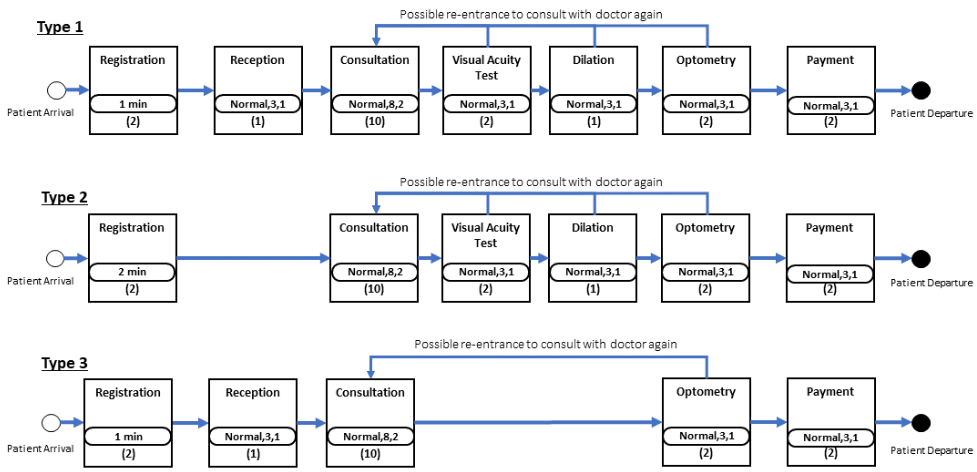

Fig. 1: Process at the eye clinic for each of the three types of patients

3) To identify areas for process improvement and physical clinic configurations (e.g., number of service stations) for operation during pandemic conditions while managing the demand and resource constraints.

D. Assumptions

Due to COVID-19, this study assumes that the clinic only caters to patients with scheduled appointments. All patients who arrive will be attended to and complete all required services or steps. It was also assumed that all staff (including doctors) are present and available throughout the entire simulation. Time to failure is not included as part of the study. All fixed resources are assumed to follow normal distributions using empirical data derived by domain experts. The domain experts are operations staff running the clinic who we have gathered information from. Finally, all consultation rooms are able to serve all patients, regardless of their conditions, race, gender and types. The travel distances are taken into consideration as part of the floor plan layout in our simulation model. The distances are based on the simulation software's setting, e.g., one grid represents one metre. The layout of the clinic is depicted in 2. The clinic has 10 consultation rooms and 2 optometry rooms and 1 dilation room.

IV. Approach

Figure 3 shows a systematic approach which we have taken. Firstly, data were collected from the systems and consulted with the domain experts. The data were then analysed to derive the input models and to frame a reasonable set of assumptions as the boundary for the 'as-is' DES model. Then, based on the additional protocols and regulations required by MOH, we designed the 'to-be' processes for operation under the pandemic situation. The various 'to-be' models were then examined and evaluated using DES. In additional, design

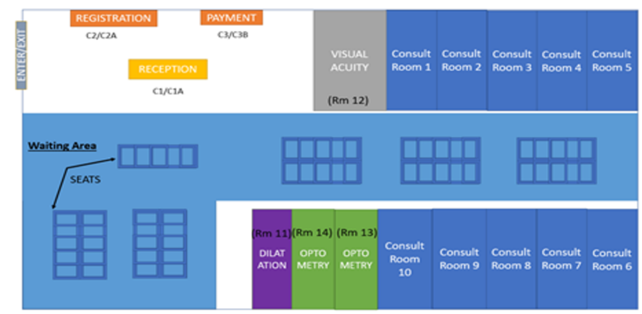

Fig. 2: Layout of the paediatric eye clinic

of experiments and optimisation were deployed to find the configuration of the clinic and process improvements that can be deployed to the clinic to cope with the demand. All simulation models were built using a discrete-event simulation software, FlexSim.

A. Input Models

We analysed the historical data from the queue system to obtain the input distributions for our simulation model using a software called 'ExpertFit'. In addition, expert's advice was sought for cases which distribution-fitting were not straightforward. Clinic staff provided the service time duration information and recommendations based on an aggregated system queue data that was gathered over a month at the clinic.

The patient arrival is modelled as a time-varying Poisson process as presented in Table I. The corresponding inter-arrival times are modeled as Exponential distributions in the simulation model. The last arrival allowed at the clinic is set to 4 o'clock in the afternoon. Patients may arrive before the opening hours of the clinic.

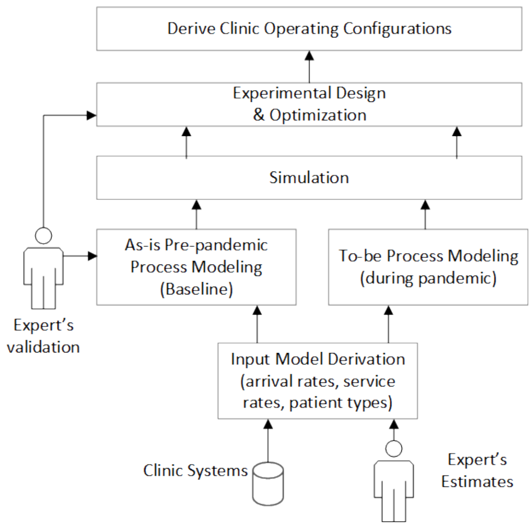

Fig. 3: The overall approach

TABLE I: Arrival rates λ (patients / hour) as time-varying Poisson processes

Time of Day	Poisson Distribution with given λ
07:00 - 08:00	25
08:00 - 09:00	45
09:00 - 10:00	50
10:00 - 11:00	30
11:00 - 12:00	35
12:00 - 13:00	45
13:00 - 14:00	40
14:00 - 15:00	20
15:00 - 16:00	10

Table II depicts the distributions used in our 'as-is' model based on each of the activities in the process. Each distribution uses a unique random number stream in the simulation software to ensure we can replicate the values for fair comparisons with 'to-be' models.

TABLE II: Service times for each activity

Activity	Service Times (Normal Distributions)
Registration	mean μ: 3min, std. dev. σ: 1 min
Reception	mean μ: 3min, std. dev. σ: 1 min
Visual Acuity	mean μ: 3min, std. dev. σ: 1 min
Optometry	mean μ: 3min, std. dev. σ: 1 min
Consultation	mean μ: 8min, std. dev. σ: 2 min
Dilation	mean μ: 3min, std. dev. σ: 1 min
Payment	mean μ: 3min, std. dev. σ: 1 min

To identify the proportions of the 3 patient types, the data from the queue system queue were again analysed, and the relative percentages of Types 1, 2, and 3 were found to be 50%, 30%, and 20%, respectively. During the visit, patients may consult doctor multiple times (we call this re-entrance). For example, after Optometry services, patient may be required to return to the consultation queue to wait for another round of discussion with the doctor. We examined the historical data and the percentages of visiting the doctor once (i.e., no re-entrance), twice (i.e., 1 re-entrance), and thrice or more ($>$ 1 re-entrance) are 53%, 41%, and 6%, respectively.

B. Key Performance Indicators (KPIs)

Performance indicators measure the output of the DES model and commonly include patient throughput, timeliness of care (i.e., extent of waiting) and resource utilization. For the eye clinic, one of the key performance indicators used in the industry is the satisfaction level for each patient, which is indirectly linked to the timeliness of care. In general, this indicator is affected by the overall stay-time in the clinic, i.e., the amount of time the patient had spent in the facility. In this study, the key performance indicators being considered are given below. s, P_n, and $\overline{\lambda}$ refer to the number of servers (e.g., counters), the probability of n people in the system, and the average arrival rate over the long run, respectively.

1) Average Wait-Time in Consultation Queue W_q: The average time spend waiting in the queue for consultation (in minutes), which is calculated by

$$W_q = \sum_{n=s}^{\infty}((n-s) \times P_n)/\overline{\lambda} \tag{1}$$

2) Average System Stay-Time (daily average) : The average amount time patients spent in the clinic (in minutes), which is calculated by

$$W = \sum_{n=0}^{\infty}(n \times P_n)/\overline{\lambda} \tag{2}$$

3) Throughput (daily average): The average number of patients served per day, which is calculated by

$$L = \sum_{n=0}^{\infty}(n \times P_n) \tag{3}$$

4) Total 60-Day Throughput: The total number of patients served $L \times 60$ days of simulation.

V. As-Is Pre-COVID Process Analysis

A. As-Is Simulation Model

The 'as-is' DES model is depicted in Figure 4. The model was structured based on the estimated distance between stations derived from the floor plan as per Figure 2. We then simulated the process for 60 days. The lunch time for the staff was configured to stagger between 11 am – 2 pm.

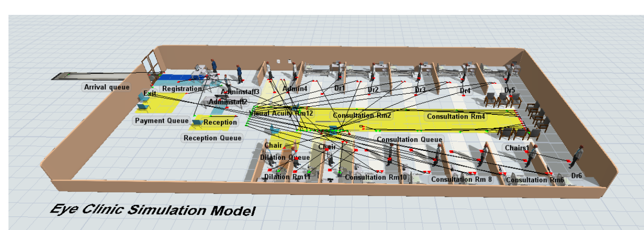

Fig. 4: A snapshot of the as-is simulation model

The simulation boundary starts from the point a patient arrives at the eye clinic to the point where the patient leaves the clinic. The following lists the system components used in our simulation model:

1) System Entity: Patient
2) Attributes: Patient Type, i.e., Type 1, 2 and 3 as per Figure 1
3) Activities: Registration, Reception, Consultation, Visual Acuity, Dilation, Optometry, Bill Payment as per Table II
4) Events: Arrival at the clinic and Departure from the clinic
5) State Variables: Number of patients in the waiting area, Number of busy consultation rooms, Number of busy doctors, Time spent in the system by each patient

The results of the simulation of 'as-is' model is presented as part of the analyses for the 'to-be' models in Section VI.

B. Validation of As-Is Process

To ensure that the 'as-is' simulation model serves as the baseline for comparisons with the to-be models, we conducted interviews with domain experts and performed experts' validation on the results. The clinic staff reviewed the simulation runs and the output from the simulation dashboard and acknowledged that the overall performance of the simulation model based on the KPIs in Section IV-B were representative of the performance of the actual physical clinic.

VI. Re-designing Clinic Under Pandemic Conditions

MOH has mandated that all healthcare facilities incorporate (1) safety and quota checks before patients be allowed to enter the clinic and (2) ensure social-distancing within the clinic's premise and shorter wait-time to reduce possibility of inter-mingling between patients or caregivers. (3) In addition, due to border closure and diversion of resources to other parts to support emergency services, the clinic could sometimes face challenges in availability of healthcare manpower resources. The clinic must adapt accordingly and adhere to the regulations. Therefore, redesigning the clinic for pandemic is required. With the above requirements, we evaluate the following three scenarios:

1) Scenario A: The clinic's new configuration for additional safety check at the entrance.
2) Scenario B: The new configuration and capacity that can be supported by the clinic due to safe-distancing measures.
3) Scenario C: Potential process improvements and possibility of combining some services in the clinic with use of shared resource.

A. Additional Safe Entry Checks

The clinic must implement an additional station at the entrance to perform safe-entry checks for contact-tracing purposes and ensuring that patients have valid appointments with at most one caregiver. The check process is shown in Figure 5. After consulting with the experts at the clinic, these steps can be implemented via an additional station with multiple counters. 80% of the patients cleared the process within 2 minutes, and the remaining 20% whose appointments are not found in the system may take up to 10 minutes, uniformly distributed. We modify the 'as-is' model to accommodate the additional station outside the clinic. The simulation model is as shown in Figure 6.

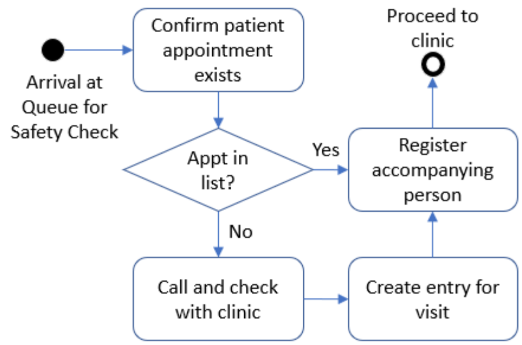

Fig. 5: Additional safe entry process at the entrance

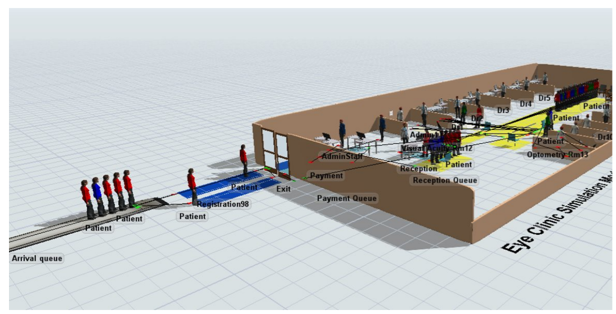

Fig. 6: Simulating additional two-station safety checks at the entrance

We conducted an experiment using 30 replications for 4 different scenarios with 1,2,3 and 4 check-in counters based on 60-day simulation runs. Shown in Table III, we observed that beyond 2 counters, the queue length and average queue stay-time of the safety check station did not have any further improvements with additional counters.

Next, we evaluate the impact of the safety-check station on the clinic's performance based on the KPIs listed in Section IV-B. The results are presented in Table IV. Take note that the system stay-time includes the time spent in the safety check station. The results showed that the system stay-time has increased by about 13% which is understandable since there are additional checks involved. The daily and 60-day throughput results are comparable to the baseline model. An interesting insight is that the average wait-time at the consultation queue has decreased. We infer from our analysis that the clinic sees only patients with appointments and verification of appointment were done at the safety-check station, hence shortening the wait. Procedures at registration and preparation work were also made smooth with patients with appointments. From this analysis, we believe that the additional safety check station will be able to cater to similar demand patterns prior to the pandemic period.

TABLE III: Results for the multi-counter safety-check station (Scenario A)

		Mean	Sample Std Dev	Min	Max
Average Safety-Check Queue Length	1 Counter	190.4	25.0	162.1	219.0
	2 Counters	24.0	2.7	21.3	28.2
	3 Counters	20.6	2.8	18.0	25.2
	4 Counters	19.9	2.8	17.4	24.3
Average Safety-Check Queue Stay Time	1 Counter	882.6	110.7	757.9	1019.4
	2 Counters	104.3	8.0	95.5	117.1
	3 Counters	89.8	9.0	80.8	104.2
	4 Counters	86.5	9.0	78.1	100.5

TABLE IV: KPIs for adding safety check station (Scenario A)

Results	Baseline	1	2	3	4
Average Wait-Time in Consultation Queue/mins W_q	24.18	10.44	10.53	10.62	10.99
Average System Stay-Time(average daily)/mins W	217.27	248.80	247.8	246.7	246.61
Throughput(average daily)/number L	306	305	304	304	304
Total 60-day Throughput $L \times 60$	18332	18272	18239	18244	18255

B. Reduced Capacity for Safe-Distancing

Depending on the prevailing spread within the community, MOH requires the clinic to adapt and limit the number of patients due to safe-distancing measures. This scenario explores the optimal number of patients to be scheduled for appointment, as a percentage of the original capacity in the 'as-is' model. As we have also added additional health and travel declaration processes at the registration, and a sanitization step at the service stations due to the additional hygiene requirements, we anticipate that the process may take a longer time to complete. Therefore, our analysis in this section shall evaluate the impact of these additional processes during the pandemic and conduct a sensitivity analysis based on arrival rates to help decision-makers strike a balance between serving as many patients as possible while satisfying the safety and the operational wait-time requirements.

We investigated the pandemic process by handling 90%, 80% and 70% of the pre-pandemic demand at the clinic and capturing the corresponding key performance indicators. The arrival rates, λ, of each of the scenarios is apportioned by the percentages. Similarly, simulations were run for 30 replications over 60 days, and the results based on the KPIs are presented in Table V.

C. Cross-Trained Staff and Combined Station

In this scenario, we examined a modification of the 'as-is' model to use shared resources across multiple services. We evaluated the stations in the clinic which used similar resources and found that Visual Acuity and Dilation stations were the possible stations to be combined as a single station with shared resources. We connected the three rooms in the clinic in the simulation, then combined them to the same queue. We constructed an experiment using 30 replications over 60 days, and simulated the process using different numbers of combined stations. We investigated 1 to 4 combined stations. The results are summarized in Table VI. It was observed that beyond 2 combined stations, any additional station no longer has a significant impact on the system stay-time,

VII. Recommendations

A. Discussions

Based on our findings in Section VI, we recommend that the clinic implements two counters at the entrance to perform the additional safe-entry and quota checks. From our observations, there is no significant improvement in terms of wait-time at the entrance with additional safety check counters beyond two.

Based on results shown in Table V, the more we reduce the percentage of arrivals, λ, the lower the KPIs values are. The throughput that can be handled by the system is proportionally lower than the 'as-is' model which is understandable due to the reduced capacity under pandemic conditions. The observations indicate the trade-off between lower throughput for shorter wait-time in queue and stay-time in the system. It is worth noting that nevertheless, the KPIs satisfy requirements set by the hospital, for example the wait-time requirement is below 30 minutes. The model and results shall serve as guiding principles for decision-makers in choosing an appropriate percentage of reduction of patients based on prevailing state of transmission of the COVID-19 virus and policies set by MOH.

For further improvement in our process to cope with resource crunch during the pandemic, we recommend that the Visual Acuity and Dilation services could be combined and use shared resources. We recommend that the clinic sets up two stations to cater for the demand. It is noted there was no further improvement to the performance measures by going beyond two stations. By combining the two services, the clinic can reduce one administrative staff and still able to cope with the demand at the clinic. To implement this improvement, the ophthalmic nurses need to up-skill to take on additional duties such as administering the dilation eye-drops.

B. Further Optimisation of To-Be Process

In the 'as-is' analysis, we observed that there were some idle consultation rooms. As doctors are considered as expensive resources, we further investigate the optimal combination of visual acuity cum optometry stations as well as the number of consultation stations that the clinic should operate. We used a

TABLE V: KPIs for scenario with reduced capacity (Scenario B)

Results	**Base λ**	**λ = 90%**	**λ = 80%**	**λ = 70%**
Average Wait-Time in Consultation Queue/mins W_q	24.18	20.86	18	14.25
Average System Stay Time(average daily)/mins W	217.27	184.79	152.04	121.44
Throughput(average daily)/number L	306.00	276.00	248.00	221.00
Total 60-day Throughput $L \times 60$	18332	16546	14899	13254

TABLE VI: KPIs for combined station providing Visual Acuity and Dilation services (Scenario C)

Results	Baseline	1 Station	2 Stations	3 Stations	4 Stations
Average Wait-Time in Consultation Queue/mins W_q	24.18	30.72.44	30.65	30.64	30.70
Average System Stay Time(average daily)/mins W	217.27	139.34	138.41	138.06	139.52
Throughput(average daily)/number L	306	304	304	277	292
Total 60-day Throughput $L \times 60$	18332	18240	18217	16642	17517

simulation optimization component in the simulation software to seek the optimal number of resources for consultation, visual acuity and optometry stations that minimizes average system stay-time. The optimiser was set up to be 'discrete' for our decision variables. The set-up assumed 1 resource to 1 station. The optimization solution revealed that the optimal number of visual acuity cum optometry station is 2, while optimal number of consultation stations is 7. From our subsequent correspondence with the clinic, the suggested optimal number of doctors is consistent with the current practice at the clinic which often uses 7 active consultation rooms.

VIII. Conclusion

In a rapidly changing healthcare environment, especially due to the COVID-19 pandemic, the healthcare systems face pressures to make their service competitive through operational and strategic decision-making. In this study, we proposed a systematic approach based on the Discrete Event Simulation as a data-driven method to build a prescriptive model based on real-world data and expert's view to support decision-making at the paediatric eye specialist clinic in Singapore during the pandemic.

Through our model, we provided meaningful insights to the operating configurations required to operate the clinic safely, effectively and efficiently, while satisfying the safety, throughput and wait-time requirements set by the authority or the clinic. We believe that our contributions pave way to agile designs of healthcare processes, be potentially extendable to other health clinics and be able to respond to the needs of the public in a smart city.

For future work, we plan to further improve the simulation model by including more patient types (e.g., urgent cases), policy-based improvement scenarios (e.g., slot-based appointment) and so on. We may also include more advanced technologies such as digital twin. We hope to validate the model by deploying our proposed designs and perform further analysis for improvements to better serve the young citizens in our city.

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