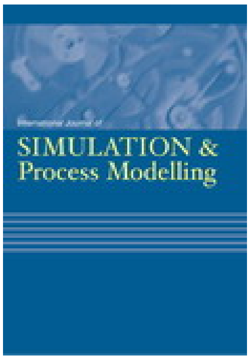


International Journal of Simulation and Process Modelling

ISSN online: 1740-2131 - ISSN print: 1740-2123
https://www.inderscience.com/ijspm

Patient waiting time analysis in a multi-specialty ophthalmic outpatient clinic using data analysis and discrete event simulation

Shanmugam Prasanna Venkatesan, Lalwani Saurabh, Naveen Thomas, Sumanta Roy

DOI: 10.1504/IJSPM.2023.10056150

Article History:

Received:	01 December 2022
Last revised:	25 March 2023
Accepted:	06 April 2023
Published online:	26 October 2023

Patient waiting time analysis in a multi-specialty ophthalmic outpatient clinic using data analysis and discrete event simulation

Shanmugam Prasanna Venkatesan*, Lalwani Saurabh, Naveen Thomas and Sumanta Roy

Department of Production Engineering,
National Institute of Technology,
Tiruchirappalli, Tamil Nadu, India
Email: prasanna@nitt.edu
Email: lalwanisaurabh9@gmail.com
Email: kngtnitt@gmail.com
Email: sumanta.roy093@gmail.com
*Corresponding author

Abstract: The demand for outpatient services is rapidly growing, resulting in multifaceted challenges due to capacity limitations. This research aims to analyse the patient waiting time in a multi-specialty ophthalmic outpatient clinic using data analysis and discrete event simulation (DES). The patient arrivals, the duration for pre-consultation and post-consultation services are highly uncertain. At first, a linear regression analysis is performed using electronic health record (EHR) log data, and the significant factors that affect patient waiting time are found. Further, a discrete event simulation model of the outpatient clinic is built using FlexSim Healthcare software (5.3) and validated. Improvement scenarios, namely: 1) adding resources; 2) introducing fixed interval appointment scheduling; 3) combining scenarios 1 and 2, are proposed for reducing the patient waiting time and evaluated. From the simulation results, it is inferred that scenario 3 reduces the average waiting time of the patients to 12.45 minutes from 38.37 minutes.

Keywords: healthcare simulation; outpatient clinic; ophthalmology; data analysis; regression; waiting time.

Reference to this paper should be made as follows: Venkatesan, S.P., Saurabh, L., Thomas, N. and Roy, S. (2023) 'Patient waiting time analysis in a multi-specialty ophthalmic outpatient clinic using data analysis and discrete event simulation', *Int. J. Simulation and Process Modelling*, Vol. 20, No. 1, pp.10–20.

Biographical notes: Shanmugam Prasanna Venkatesan is an Associate Professor in the Department of Production Engineering at the National Institute of Technology, Tiruchirappalli, India. His research interests include Healthcare simulation, E-waste management, and supply chain risk modelling.

Lalwani Saurabh obtained his Master's in Industrial Engineering and Management from the Department of Production Engineering at the National Institute of Technology, Tiruchirappalli, India. His research interest is in Healthcare simulation.

Naveen Thomas obtained his Undergraduate in Production Engineering from the National Institute of Technology, Tiruchirappalli, India. His research interest is in FlexSim Healthcare simulation.

Sumanta Roy obtained his MS in Research from the Department of Production Engineering at the National Institute of Technology, Tiruchirappalli, India. His research interest is in healthcare simulation.

This paper is a revised and expanded version of a paper entitled 'Waiting time reduction in a hospital outpatient clinic using flexsim simulation' presented at XXIII Annual International Conference of the Society of Operations Management (SOM2019), Industrial & Management Engineering Department, Indian Institute of Technology Kanpur, India, 19–21 December 2019.

1 Introduction

An outpatient clinic is a standalone private or public healthcare facility (can be a part of a hospital) that provides various services (e.g., screening and treatment of patients, follow-up of discharged patients, consultation, diagnostic tests, and minor surgical procedures) to different patient classes every day, without an overnight stay (Akin et al., 2013; Hong et al., 2013). It is generally handled by consultant physicians who also attend to inpatients in the wards. Many patients are examined and treated as outpatients before being admitted to the hospital as inpatients at a later date. When discharged from hospitals, inpatients also receive follow-up treatment in outpatient clinics. Follow-up outpatient clinic services such as consultations, treatments, diagnostics, and patient follow-up are often grouped in unique locations in outpatient clinics (Roy et al., 2021). The existing literature on outpatient clinics focuses on the general outpatient clinic (GOPC) and specialist outpatient clinic (SOPC). The GOPC refers to a non-specialised healthcare provider offering primary and general treatment for patients with all medical conditions. GOPC providers offer diagnostic services, patient screening for referrals, and treatment for ailments that do not need any specialist consultation. The SPOC clinics include those dedicated to specialty services such as orthopaedics, surgery, paediatrics, ophthalmic, obstetrics and gynaecology. The research on SPOC is fairly developed due to the rapid growth of specialised hospitals with better amenities. The increased demand for outpatient clinics has contributed to overcrowded clinics and patient dissatisfaction. Computer modelling and simulation (M&S) can help decision-makers meet the operational challenge of balancing the demand for outpatient services with considerations of available capacity. M&S allows for the experimentation of strategies to improve metrics associated with productivity and efficiency (Crema and Verbano, 2021; Ershadi and Shafaeizadeh, 2021), patient throughput, and waiting time (Naiker et al., 2018; Shoaib and Ramamohan, 2020), and service quality (Roy et al., 2020). Appointment systems, resource allocation, and patient flow management in outpatient clinics affect patient waiting time and resource utilisation (Hong et al., 2013; Heshmat et al., 2023).

The mean waiting time of a patient in a facility is a significant measure used to determine the efficiency of healthcare delivery. Waiting time in hospital outpatient clinics affects patient satisfaction, access to care, trust, willingness to return, and hospital revenue. Researchers aim to reduce waiting times to improve patients' satisfaction, and some have used simulation techniques to suggest ways of reducing the waiting time. Past studies have explored the length and variability of patient's waiting times and reported that patients who were given expected waiting times were more satisfied than those who were not (Sriram and Noochpoung, 2018). This research aims to analyse the patient waiting time in a multi-specialty ophthalmic outpatient clinic using data analysis and discrete event simulation (DES). At first, a linear regression analysis is performed using electronic health record (EHR) log data, and the significant factors that affect patient waiting time are obtained. Further, a DES model of the outpatient clinic is built using FlexSim Healthcare software (5.3) and validated statistically. Improvement scenarios, namely:

1 adding resources
2 introducing fixed interval appointment scheduling
3 combining scenarios 1 and 2, are proposed for reducing the patient waiting time and evaluated.

An ophthalmology clinic is considered in this research as the waiting time is generally higher than other specialists' OPC because of the patients' age group and the increased number of patients (Mohebbifar et al., 2014). The remainder of this research is organised as follows. Section 2 presents the literature review. The problem description and proposed methodology are presented in Sections 3 and 4, respectively. The result and discussion are reported in Section 5. Finally, conclusions and areas of further research are discussed in Section 6.

2 Literature review

The increasing popularity of DES in healthcare has increased the volume of literature. The recent studies on the ophthalmic outpatient clinic are summarised in Table 1. The literature is classified based on the issue addressed, research objective, simulation method, and software used. Following Aby et al. (2022), the issues addressed are broadly categorised as

1 appointment scheduling
2 patient flow/routing
3 resource allocation.

The appointment scheduling decisions analyse the impact of

a appointment rule (Luo et al., 2016; Lin et al., 2017; Munavalli et al., 2020a, 2020b)
b patient type (Al-Araidah et al., 2012; Munavalli et al., 2017; Hribar et al., 2017; Demir et al., 2018; Lowalekar and Ravichandran, 2019)
c adjustment policies such as overbooking, same-day appointments, real-time scheduling, to reduce the disruptive effects of walk-ins, no-shows, and emergency patients (Pan et al., 2015).

The appointment rule determines the slot for patients to reduce the waiting time. Appointment rules reported in the literature include individual block/fixed interval (IBFI), OFFSET, DOME, 2BEG, multiple block/fixed interval (MBFI), 2BGDM, MBDM (Hong et al., 2013). Typically, patients are classified into manageable groups based on their arrival (new, follow-up, and transferred), age, sex (male, female), and physical mobility.

Patients in an outpatient clinic go through various medical services/pathways such as registration, pre-consultation, consultation, post-consultation, payment, and booking appointments for the next visit before checkout. Information flow and patient flow are interrelated throughout patient pathways. Variation of services required by each patient and variation of each service duration complicate patient pathways and pose a challenge in ensuring optimal patient flow. Controlled patient flow can significantly reduce patient waiting time and improve resource utilisation. Pathway-based (Demir et al., 2018; Munavalli et al., 2020a), schedule-based (Pan et al., 2015; Hribar et al., 2017; Munavalli et al., 2020b), and resource-based (Al-Araidah et al., 2012; Munavalli et al., 2017; Lin et al., 2017); Chabouh et al. (2017) approaches are proposed in the literature to improve patient flow. From Table 1, it is identified that resource-based improvement has been used widely compared to pathway-based and scheduling-based improvements. Proper planning and allocation of resources such as beds, doctors, nurses, rooms, and equipment are essential to improve performance, such as waiting time, overtime, congestion, and resource utilisation. Healthcare services find it difficult to acquire more resources due to the rising cost, which identifies ways to improve the usage of existing resources such as doctors, staff, and equipment (Ordu et al., 2020). Zhu et al. (2012) evaluated the possible causes for the increased waiting time using DES and suggested four possible improvement scenarios, namely distribute the appointment slots evenly over the whole session, start the session on time, remove the unused session time during the session and remove the irregular calling sequence. Jin et al. (2013) used a data-driven simulation model with FlexSim Healthcare to reduce the waiting time for consultation in an outpatient clinic by suggesting strategies relating to appointment scheduling, changing the arrival pattern, and the process flow. They found that patients' irregular arrival pattern during the day is one of the leading causes of the long waiting time. Naiker et al. (2018) have identified numerous strategies, consolidated them into 26 approaches, and further reported three themes, resource realignment, operational efficiency, and process improvement, that significantly affect waiting times. Norouzzadeh et al. (2015) formulated and validated a DES model to improve resource utilisation, and patient turnaround time considering resource allocation, patient rooming and prioritisation, and patient volume strategies. Mocarzel et al. (2013) proposed a simulation model for multi-specialty outpatient healthcare and investigated different resource allocation policies considering patient and management performance measures. Table 1 shows that DES is the most commonly used simulation approach, followed by hybrid simulation optimisation. Among the commercial off-the-shelf (COTS) simulation software, Arena is the most widely used tool within the reviewed articles. It is also observed that a few researchers use .NET framework and Java programming tools. Our analysis further suggests the secondary use of the information such as EHR in DES modelling have not received much attention. An information system such as EHR could generate a large data set representing the patient flow and resources within a healthcare system. This necessitates the use of big data analytics (BDAs) techniques such as process mining, machine learning, and data mining to facilitate stages of the DES methodology.

In recent years the DES combined with the BDAs approaches of data mining, machine learning, data farming, visual analytics, and process mining has been attempted (Greasley and Edwards, 2019). Lin et al. (2020) have tested machine learning models to predict wait times based on EHR data in outpatient clinics. Belayneh et al. (2017) used linear regression and bivariate logistic regression to identify variables that affect the patient waiting time in a general outpatient department and further reported that the major causes of the long patient waiting time are large numbers of the patient with few doctors, long searching of the patient cards and long registration time. Mohebbifar et al. (2014) analysed the outpatient waiting time and reported that the registration procedure, medical doctor shortage and skilled staff are the significant factors. Ahmad et al. (2017) assessed patient waiting time and doctor consultation time in a primary healthcare clinic through sampling methods and offered suggestions for improvement. Anderson et al. (2007) found that the combination of a long waiting time to consult the doctor and to have a short doctor visit is associated with much low overall patient satisfaction, and the decrement in satisfaction related to long waiting times is substantially reduced with the increment of time spent with the physician (five minutes or more). Joseph et al. (2017) have compared the performance of machine learning tools and conventional techniques like linear regression and decision tree to predict the treatment durations and overall waiting time of patients. Billing et al. (2007) identified positive correlations between patient-estimated waiting time, ratings of waiting times, booking efficiency, intention to return, to comply with the advice given, and higher ratings of the overall quality of the service and satisfaction levels. Omotoye et al. (2017) analysed the factors responsible for the waiting time of patients in an ophthalmic outpatient clinic and reported that follow up patients spend less time than new patients. From the above, it is observed that simulation modelling of the outpatient department using secondary EHR data deserves research attention. The availability of a set of EHR data representing the patient flow and resources within a healthcare system enables the application of data analytics techniques such as process mining, machine learning, and data mining to facilitate stages of the DES methodology. This research aims to fill this gap and analyse the patient waiting time in a multi-specialty ophthalmic outpatient clinic using regression and DES. As our main contribution, we develop a DES model of an outpatient ophthalmology clinic to improve the patient waiting time using secondary EHR data. Considering the high volume of patients with medical and surgical needs, the ophthalmic healthcare setting is an ideal domain for the present study. Our research aims to provide insights into the benefits of adding resources such as examination rooms, as well as strategies for improving patient scheduling.

Table 1 Recent literature on ophthalmic outpatient clinic simulation

Sl no.	*Author and year*	*Issue addressed*			*Research objectives*	*Simulation approach*	*Package/software used*
		Appointment scheduling	*Patient flow/routing*	*Resource allocation*			
1	Al-Araidah et al. (2012)	Scheduled/ walk-ins	Resource-based	Doctor, staff	Waiting time and length of stay	DES	Arena
2	Pan et al. (2015)	Patient no show, Patient unpunctuality, overbooking	Schedule-based	Equipment, staff, station sharing	Patient flow and turnaround time	DES and DOE	FlexSim Healthcare
3	Hribar et al. (2016)	No show, overbooking	Resource-based	Staff, room, doctors	Average exam time and average wait time	DES with EHR data	Arena
4	Luo et al. (2016)	Patient unpunctuality, appointment rule	Pathway-based	-	Waiting time	DES	--
5	Munavalli et al. (2017)	Walk-ins	Resource-based	Staff, equipments	Waiting time and cycle time	Simulation optimisation	Java
6	Hribar et al. (2017)	Walk-ins	Schedule-based	Staff	Waiting time and clinic efficiency	DES with EHR data	Arena
7	Lin et al. (2017)	Appointment rule, patient punctuality	Resource-based	Doctor, staff	Resource overtime, patient waiting time	Simulation optimisation	.NET platform
8	Hribar et al. (2018)	-	Resource-based	Physician, staff	Average waiting time	DES with EHR data	Arena
9	Demir et al. (2018)	Patient type	Pathway-based	Staff, room bed, equipment	Service quality	DES	--
10	Fricks et al. (2018)	-	Resource-based	Staff	Clinic flow	DES	MATLAB
11	Chabouh et al. (2017)	Appointment rules, patient type	Resource-based	Staff, bed, room	Patient waiting time and expected surgical suite completion time	Simulation optimisation	Arena
12	Lowalekar and Ravichandran (2019)	Walk-ins, patient unpunctuality	-	Staff	Throughput, capacity and patient wait time	Theory of constraints and DES	Arena
13	Munavalli et al. (2020a)	Walk-ins, appointment rule	Resource-based and pathway-based	Staff and doctors	Patient waiting time and cycle time	Multi-agent simulation optimisation	.NET platform
14	Munavalli et al. (2020b)	Walk-ins appointment rule	Schedule-based	-	Patient waiting time and resource utilisation	Simulation optimisation	Java

3 Problem description

The increase in the ageing population and population growth pose significant challenges to eye care systems. Recent global data showed that there are 36 million blind and 217 million with moderate or severe visual impairment (Khanna et al., 2020). This research is based on the data collected from a Multi-speciality Eye Hospital in Tiruchirappalli, Tamil Nadu, India, which is one of the NABH (National Accreditation Board for Hospitals and Healthcare Providers) certified eye care hospitals. Established in 1936 with the vision to give people quality and cost-effective eye care, the hospital currently manages 150,000 outpatients, 20,000 surgeries, and 2,500 laser procedures annually. The ophthalmic hospital consists of a registration counter, refraction, consultation, and general eye check-up on the ground floor, followed by specialists related to the retina, and cornea located on the first and glaucoma on the second floor, respectively. More than half of the arriving patients are treated as an outpatient. The healthcare providers include general and specialist ophthalmologists, optometrists, nurses, pharmacists, receptionists, records, and medical officers. The hospital is operational for six days (Monday–Saturday) a week, and the number of outpatients arriving varies on each day of the week. The hospital opens at 8.00 a.m. and closes at 5.00 p.m. with a lunch interval from 1 p.m. to 2:30 p.m.

currently, the appointment system is not followed in the clinic, and patient arrivals are random and dynamic.

Similarly, considering the individual patient's condition, the required set of pre-consultation and post-consultation services and their duration is highly uncertain. This variation complicates the patient pathways, further affects the service rate, and increases the waiting time. The major problems faced by the clinic are:

1 the patient wait times are high and variable

2 complexity in patient flow

3 long queues are being built at the common resources, which result in overcrowding.

The outpatient department reported an average waiting time of more than 40 minutes, resulting in the patient dissatisfaction about the service quality. The hospital management is concerned about reducing the patient waiting time in order to increase the throughput and patient satisfaction. The objectives of this research are

1 To identify the factors that are most significantly affecting the waiting time of a patient in an outpatient clinic using data analysis

2 To build a simulation model to identify the areas where the waiting time of a patient is intolerably high (bottlenecks)

3 To propose scenarios to reduce the overall average waiting time of the patient.

There are two types of patients (first-time and follow-up), and the typical patient flow is shown in Figure 1. The individual patients' pathway may include six chronological steps:

1 registration

2 computer eye-testing

3 optometry

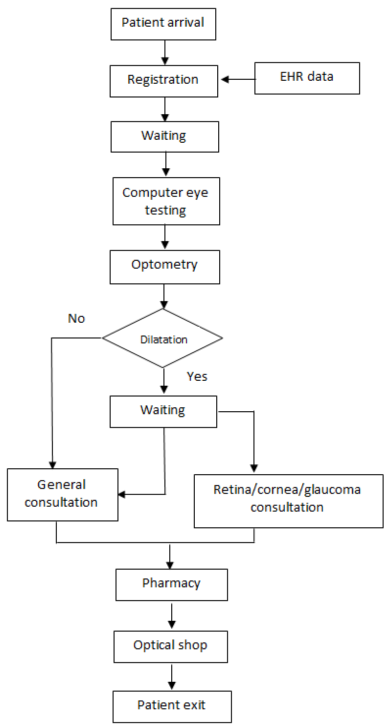
4 general or specialist consultation services

5 post-consultation services such as a visit to the pharmacy and optical shops.

These stages are described below.

- *Registration:* A new patient who visits the clinic for the first time will be asked to fill out their personal details in a registration form. One of the receptionists documents the completed registration forms and creates a unique identity medical record (MR) number for each patient through EHR. Typically, a patient's demographic details, like gender, age, type, and visit date and time of arrival, will be recorded. A follow-up patient will provide his/her MR number at the registration counter, and a receptionist will retrieve the patient medical information, which will be transferred to different stations by staff/nurses. Patients were then charged the consultation fee by one of the receptionists.
- *Computer eye-testing:* The arriving patients used to wait in the outpatient waiting area until called in for a preliminary computer eye-testing to check their vision.
- *Optometry:* Next to computer eye testing, the patient's eyesight was tested, and an optometrist conducted other basic examinations.
- *General or specialist consultation services:* A patient may consult a general or a specialist ophthalmologist (retina/cornea/glaucoma) depending on the symptoms and diagnosis. Before consulting the ophthalmologist, the patient's eye may be dilated. The nurses in the outpatient department waiting area will do the dilation by administering eye drops.
- *Post-consultation services:* After the evaluation by the ophthalmologist, the patient may require post-consultation services such as visiting the pharmacy, optical shop, billing, etc. which may vary from patient to patient. This marks the end of the patient pathway.

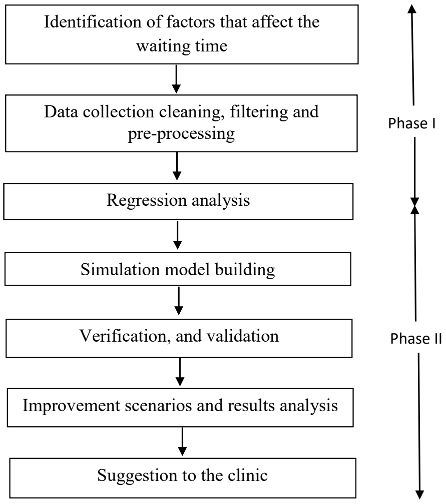
Figure 1 Typical patient flow in the ophthalmic clinic



4 Proposed methodology

The proposed methodology consists of two phases, as shown in Figure 2. In phase-I, a multiple linear regression analysis is performed using EHR log data, and the significant factors that affect patient waiting time are obtained. In phase II, a DES model of the outpatient clinic is built using FlexSim Healthcare (5.3) and validated statistically. Improvement scenarios are proposed for reducing the patient waiting time and evaluated.

Figure 2 Proposed methodology



4.1 Factors affecting waiting time using multiple linear regression

- *Study variables:* The patient's demographic details like gender, age, distance, treatment type, day of the visit, time of arrival, education, and occupation status of the patient are the independent variables, and total waiting time is the dependent variable. The total waiting time of a patient is considered as the sum of the waiting time at various areas, such as registration, optometry, consultation, etc. during her/his visit to the clinic.
- *Data cleaning:* The EHR log data that includes the MR (unique identity) number, age, gender, distance from the clinic, visit floor number, waiting times and processing times of optometry and consultation, treatment type, day of the visit, time of arrival with the name of the physician on each day is obtained from the clinic. Further, data cleaning is carried out in Microsoft Excel, and exclusion criteria are null data, duplicate values (the same person came more than one time a day), and outliers of waiting time. After cleaning, the remaining data points are included for further analysis.
- *Descriptive statistical analysis:* The descriptive statistical study is carried out using Statistical Packages for Social Sciences (SPSS) version 21.0.0.0. The regression assumptions such as heteroskedasticity, the normality of the dependent variable, multi-collinearity, and linear regression relationship are considered in regression analysis. The significant factors that affect the waiting time of a patient are obtained.

4.2 Simulation model building and evaluation

The simulation model is built using FlexSim Healthcare 3D simulation software designed for modelling and optimising healthcare processes. FlexSim Healthcare has dashboard display features to visualise system, staff, and patient metrics during the simulation run. The expert fit and experimenter modules enable us to determine the distributions of a random variable with their relative scores and to run 'what-if' scenarios to compare different options, respectively. The following elements are used to build the simulation model.

- *Resource group:* This group contains four categories: transport, equipment, elevator, and staff.
- *Flowchart:* Different objects in the model should be well connected to give patients, and staff members access to different objects and destinations; otherwise, they may get stuck in their starting point.
- *Patient track:* It is the series of activities in the model about the exact patient flow and their interactions with different locations and objects, including their processing times, staff required, and type of activities with their priorities.
- *Patient and staff path:* The network node path is used to direct the patients and staff during their course of journey to different locations/areas; otherwise, they can take the shortest route (for, e.g., it can be walking through the walls) to the destination.
- *Model assumptions:* The model assumptions are summarised below.
  1. *Structural assumptions:*
     - a Two registration counters, and each has two receptionists.
     - b Upon the completion of registration, a nurse will escort a group of four patients from the registration area to the optometry area.
     - c Every patient coming to the hospital for the first time or after six months requires the dilation process.
     - d All patients use the lift to reach the sub-specialty departments located on the first and second floors.
     - e Patients are served on an FCFS basis (first come, first serve).
     - f Emergency and paediatric patients are excluded as they form a very low fraction of the arriving population.
     - g The hospital is operational six days (Monday–Saturday) a week, opens at 8.00 a.m. and closes at 5.00 p.m.
  2. *Data assumptions:*
     - a The processing time distribution for optometry and consultation is obtained using expert fit based on the input data collected.
     - b The time required for dilation is not included in the waiting time.
     - c The lift time is assumed as negligible.
     - d The time spent by the patients in the pharmacy and optical shop are not included.
     - e The same service time distribution is assumed for the processing in all the three floors.

Figure 3 Screenshot of the FlexSim simulation model of the ophthalmic clinic (see online version for colours)

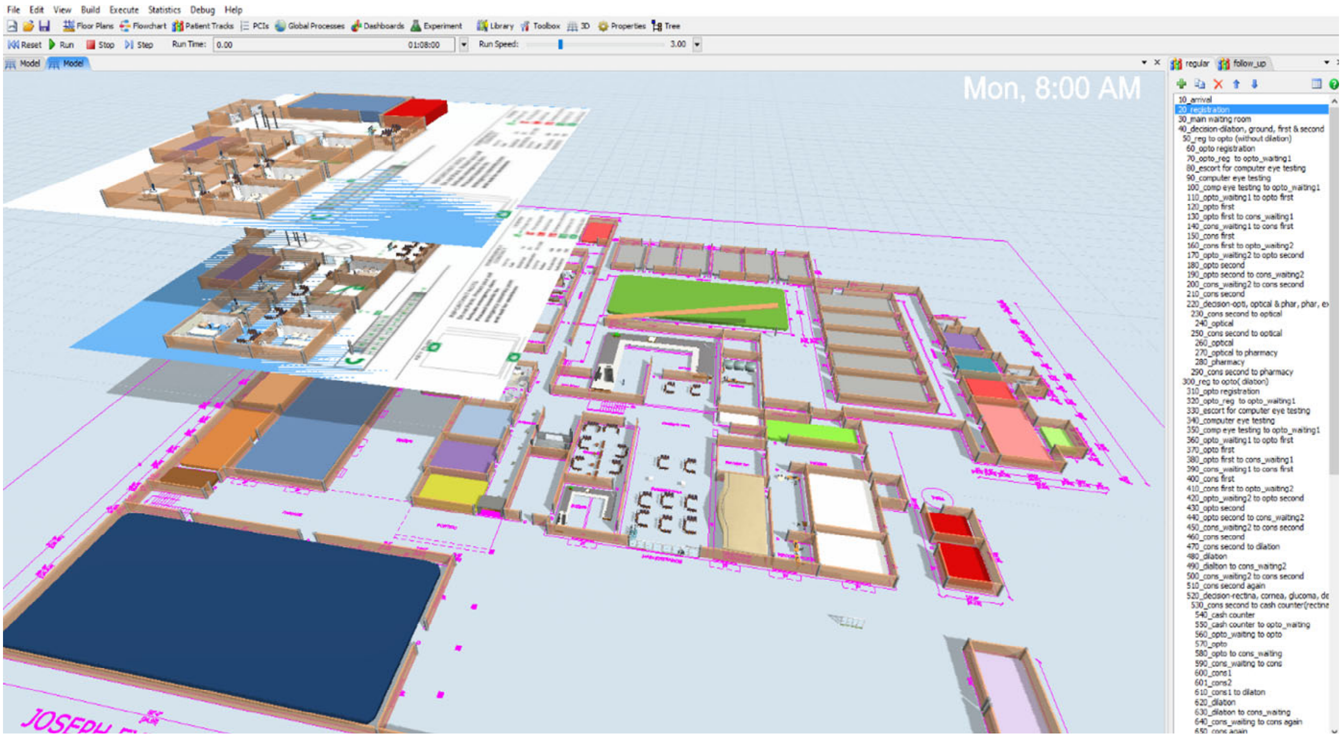


Table 2 Service time distribution (parameters) for regular patient obtained using expert fit

Service		*Optometry*	*General consultation*	*Specialist consultation*
Week day	Monday	Randomwalk (0.772, 0.770, 0.544)	Beta (0.763, 17.699, 1.045, 4.163)	Exponential (11, 7.85)
	Tuesday	Johnsonbounded (0.930, 9.802, 0.784, 0.482)	Johnsonbounded (0.472, 14.761, 1.319, 0.857)	Johnsonbounded (8.817, 46.655, 1.772, 1.222)
	Wednesday	Loglogistic (0.549, 1.300, 2.088)	Johnsonbounded (0.853, 13.682, 0.836, 0.493)	Erlang (9.826, 3.576, 3)
	Thursday	Johnsonbounded (0.617, 14.259, 1.769, 0.949)	Johnsonbounded (0.853, 13.004, 1.038, 0.581)	Johnsonbounded (9.748, 28.009, –0.009, 0.514)
	Friday	Normal (20.0, 4.0)	Exponential (0.236, 1.133)	Beta(13, 17, 0.88, 1.48)
	Saturday	Johnsonbounded (0.875, 7.002, 0.599, 0.587)	Inversegaussian (0.790, 3.522, 1.498)	Weibull (5.70408, 14.637, 2.87451)

Table 3 Service time distribution (parameters) for follow-up patient obtained using expert fit

Service		*Optometry*	*General consultation*	*Specialist consultation*
Week day	Monday	Beta (0.887, 9.182, 0.741, 1.231)	Johnsonbounded (0.617, 12.819, 0.828,0.691)	Lognormal (11, 3.68, 4.69, 0)
	Tuesday	Johnsonbounded (0.888, 16.335, 1.066, 0.477)	Exponential (0.838, 3.740)	Johnsonbounded (7.409, 33.429, 0.0001, 0.975)
	Wednesday	Loglogistic (0.756, 1.577, 2.174)	Exponential (0.048, 3.252)	Beta (10.2, 15.7, 0.532, 0.447)
	Thursday	Inversegaussian (0.684, 3.385, 1.471)	Beta (0.943, 12.159, 0.446, 0.813)	Johnsonbounded (9.884, 30.017, 0.023, 0.536)
	Friday	Lognormal2 (0.5, 1.33, 1.12)	Beta (0.5, 14, 0.519, 1.83)	Beta (7, 24, 0.809, 0.767)
	Saturday	Johnsonbounded (0.763, 19.55, 1.519, 0.663	Johnsonbounded (0.951, 11.513, 1.104, 0.368)	Beta (0.707, 30.701, 0.908, 5.127)

Table 4 Summary of descriptive statistics

Week day	*Age*								*Gender*		*Total*
	10–20	*21–30*	*31–40*	*41–50*	*51–60*	*61–70*	*71–80*	*>80*	*Male*	*Female*	
Monday	14	19	24	40	40	39	20	6	89	113	202
Tuesday	13	21	24	29	28	32	18	2	73	94	167
Wednesday	10	13	17	13	34	35	7	2	53	78	131
Thursday	9	16	11	22	21	21	6	1	49	58	107
Friday	5	12	17	27	13	26	8	2	45	65	110
Saturday	17	15	8	22	26	26	13	1	61	67	128

Table 5 Results of regression analysis

Independent variable	*Unstandardised coefficients*		*Standardised coefficients*	*t*	*Sig.*	*95 % confidence interval for B*		*Correlations*		
	B	*Std. error*	*Beta*			*Lower bound*	*Upper bound*	*Zero-order*	*Partial*	*Part*
Gender	0.013	0.070	0.007	0.194	0.84	–0.123	0.150	0.000	0.007	0.007
Age	0.055	0.022	0.102	2.523	0.01	0.012	0.097	0.092	0.088	0.087
Distance	0.005	0.028	0.006	0.168	0.86	–0.051	0.060	0.004	0.006	0.006
Week day	–0.040	0.018	–0.075	–2.166	0.03	–0.075	–0.004	–0.072	–0.076	–0.075
Registration	0.014	0.016	0.030	0.854	0.39	–0.018	0.046	0.017	0.030	0.030
Patient type	–0.133	0.070	–0.068	–1.911	0.05	–0.270	0.004	–0.044	–0.067	–0.066
Education	–0.032	0.036	–0.031	–0.880	0.37	–0.103	0.039	–0.032	–0.031	–0.030
Occupation	0.008	0.028	0.011	0.275	0.78	–0.048	0.063	0.054	0.010	0.010

- *Model building:* The screenshot of the FlexSim simulation model of the ophthalmic clinic is shown in Figure 3. At first, the AutoCAD drawings for each floor that represent the layout of the outpatient clinic is imported into FlexSim. The resources, equipment, and staff are assigned in each floor as per layout locations. A Patient Classification Index (PCI) is created for the two types of patients (first-time, follow-up) to differentiate the patients. A patient track is created for each patient type based on the patient-centred activities from the time of arrival till they exit. Typically, the patient-centred activities include:
  1. activities that the patient will do themselves
  2. activities performed by staff on the patients
  3. activities related to the patient but are performed by staff in a location other than the patient's current location (such as a nurse consulting a doctor leaving a patient in waiting area, filing a prescription, etc.).

  A network of the node is then created to define the travel path for all the patients and staff. Using the EHR log data obtained, the service time distribution of optometry and consultation is estimated using Expert fit, and the results are shown in Tables 2 and 3 for regular and follow-up patients, respectively. The service time varies with reference to the patient type and on each day of the week. However, the registration and computer eye testing time are assumed to be the same for both types of patients. A custom schedule is followed considering the average arrival for the two types of patients. The shift schedule tool feeds hospital timings and staff availability into the model.

5 Results and discussion

The collected EHR log data contained 9,554 patients' details in a typical month. Firstly, null and missing values (such as staff name) were removed, resulting in 7,935 data. We further filtered the data for every week, which resulted in an average of 1,985 patients per week.

5.1 Regression results

The regression analysis aims to establish the relation between the independent variables such as gender, age, distance, treatment type, day of the visit, time of arrival, education, and occupation status of the patient with the waiting time. We further filtered out the data from the collected EHR log data per week considering age (below 10), distance (more than 300 km), patient arrival, and waiting time values. It is observed that the number of patients visiting the clinic in the forenoon session is higher than afternoon session, and hence the analysis includes only the patient arrival from 8.00 a.m. to 12.30 p.m. Similarly, from EHR log data, the waiting time values that are less than 20 minutes and more than 200 minutes were removed as they are considered as outliers. This resulted in 845 observations for the regression analysis. The results of the descriptive analysis are summarised in Table 5. The ratio of female to male patients visiting the hospital is 44 to 56. The results suggest that among the arriving patients, 60% are follow-up and the remaining are new patients. Most of the patients visit on Monday and Tuesday, and a maximum number of patients are in the age group of 41 to 70 years. From 10 a.m. to 12 noon, a greater number of patients arrive at the hospital, resulting in increased patient waiting time during this period. The number of patients visiting the clinic on Thursday, Friday, and Saturday is found to be less. The regression analysis resulted in the independent variables age, weekday, and type of patient (regular, follow-up) are the significant factors that affect the waiting time of a patient, as shown in the coefficients Table 6.

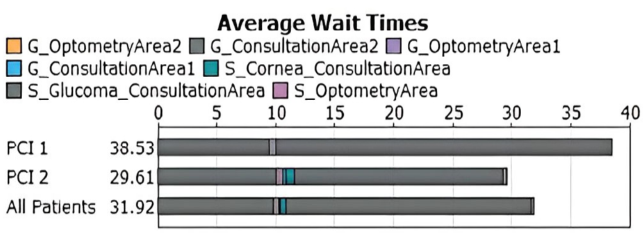
Table 6 Comparison of mean waiting time (minutes) of the proposed scenarios

Actual waiting time as per HER data	*Proposed scenarios [% reduction]*		
	Scenario 1	*Scenario 2*	*Scenario 3*
38.37	28.77 [27]	16.13 [57.9]	12.45 [67.5]

5.2 Simulation results

The developed simulation model is set to run for 4 hours per day (8.30 a.m. to 12.30 p.m.), six days per week and five replications were made using FlexSim experimenter module. Initially, the model is verified for any errors in the flowchart, patient tracking, proper assigning of processing time distribution to the right staff, and further by comparing the resource utilisation, the number of patients arrival per day. The average waiting time of new (PCI 1) and follow-up (PCI 2) patients are obtained as 38.53 minutes and 29.61 minutes, respectively. The overall mean waiting time of all the patients obtained from the model is 31.92 minutes, as shown in Figure 4. From the results, the average waiting time for the follow-up patients was found to be lower than the first-time patients as dilation is required for all the new patients as compared to follow-up patients. The model is then validated using a t-test by comparing the mean waiting time from the model with the actual waiting time obtained with EHR log data which is 38.37 minutes. From the validation results, it is observed that there is no significant difference between the model output and the actual data for the mean waiting time.

Figure 4 Mean waiting time of patients through simulation (see online version for colours)



5.2.1 Proposed scenarios

The following three scenarios are proposed for improving patient flow and reducing patient waiting time. The comparison of mean waiting time (minutes) of the proposed scenarios is shown in Table 6. The values in bracket indicates the percentage reduction in waiting time.

- *Scenario 1 adding resource:* The waiting time on the second-floor glaucoma consultation area is found to be very high. Hence, the utilisation of an additional examination room on the same floor is proposed. The simulation of this proposed strategy results in reducing the average waiting time of the patients to 28.77 minutes. As the glaucoma patients on the second floor were waiting for a long time, adding another examination room (nearby) and diverting some of the patients reduced the waiting time significantly. The simulation output suggests that the implementation of this strategy reduces the waiting time by 27%.
- *Scenario 2 appointment scheduling:* The appointment schedule is not followed at present in the hospital resulting in the random arrival of patients. To smoothen the arrival pattern, appointment scheduling is proposed. Considering the resource availability, we propose equal number of arrivals/hours in the morning session. The simulation of this strategy results in reducing the patient average waiting time to 16.13 minutes from 38.37 minutes. The appointment scheduling strategy reduces the average waiting time by 57.9%.
- *Scenario 3 combining both scenarios 1 and 2:* The combined application of strategies 1 and 2 results in reducing the waiting time significantly to 12.45 minutes from 38.377 minutes. Appointment scheduling and the addition of resources helped reduce patient waiting time by 67.5%.

The major findings of this research are:

1. The secondary use of EHR data in healthcare simulation helps to accurately model the patient flow.
2. The developed simulation model provides insight into the allocation of resources and strategies for improving patient scheduling in an ophthalmic clinic.
3. Simulation results show that a significant reduction in patient waiting time can be achieved by introducing a scheduling strategy and adding resources.

Our findings agreed with results of Hribar et al. (2017) and Kern et al. (2021).

6 Conclusions

This research aims to analyse the patient waiting time in a multi-specialty ophthalmic outpatient clinic using data analysis and DES. At first, a linear regression analysis is performed using HER log data and the significant factors that affect patient waiting time are obtained. Further, a DES model of the outpatient clinic is built using FlexSim Healthcare software (5.3) and validated statistically. The regression analysis resulted that the independent variables age, weekday, and type of patient (regular, follow-up) are the significant factors that affect the waiting time of a patient. An 'as is' model of the ophthalmic clinic is built and validated. The average waiting time for the follow-up patients was found to be lower than the first-time patients. Three scenarios are proposed for improving patient flow and reducing patient waiting time. From the results, it is observed that adding an additional glaucoma consultant and following an appointment, schedule would significantly reduce the patient waiting time and improve the patient flow. The obtained results are communicated to the hospital management for implementation. This research has a few limitations. The cost analysis is not included in this study. Patient satisfaction levels are not measured explicitly by considering the factors such as choice of physician, time slot, etc.

This work can be extended by having a dynamic model to predict the waiting time of the patient based on the patients' waiting time obtained from EHR log data. The application of process mining techniques to discover the patient flow through EHR log data could be a potential research area. Other performance metrics such resource utilisation, patient throughput and economic analysis could be included as a future scope. Future research may focus on developing dynamic/adaptive appointment scheduling models incorporating patient preferences on the choice of physician, time slot, and cancellation policy to enhance patient satisfaction levels. This research can be further extended to other areas of outpatient clinics to reduce the waiting time of patients.

Acknowledgements

The authors acknowledge the editor and the two reviewers for their constructive comments.

References

Aby, M.P., Prasanna Venkatesan, S. and Nav, M. (2022) 'Simulation modelling of hospital outpatient department: a bibliometric analysis and a literature classification', *Simulation: Transactions of the Society for Modeling and Simulation International*, In print, DOI: 10.1177/00375497221139282.

Ahmad, B.A., Khairatul, K. and Farnaza, A. (2017) 'An assessment of patient waiting and consultation time in a primary healthcare clinic', *Malaysian Family Physician: The Official Journal of the Academy of Family Physicians of Malaysia*, Vol. 12, No. 1, p.14.

Akin, G., Ivy, J.S., Huschka, T.R., Rohleder T.R. and Marmor, Y.N. (2013) 'Capacity management and patient scheduling in an outpatient clinic using discrete event simulation', *2013 Winter Simulations Conference (WSC)*, pp.2215–2226, DOI: 10.1109/WSC.2013.6721598.

Al-Araidah, O., Boran, A. and Wahsheh, A. (2012) 'Reducing delay in healthcare delivery at outpatients clinics using discrete event simulation', *International Journal of Simulation Modelling*, Vol. 11, No. 4, pp.185–195 [online] https://doi.org/10.2507/ijsimm11(4)2.211.

Anderson, R.T., Camacho, F.T. and Balkrishnan, R. (2007) 'Willing to wait?: the influence of patient wait time on satisfaction with primary care', *BMC Health Services Research*, Vol. 7, No. 1, p.31 [online] https://doi.org/10.1186/1472-6963-7-31.

Belayneh, M., Woldie, M., Berhanu, N. and Tamiru, M. (2017) 'The determinants of patient waiting time in the general outpatient department of Debre Markos and Felege Hiwot hospitals in Amhara Regional State, North West, Ethiopia', *Global Journal of Medicine and Public Health*, Vol. 6, No. 5, pp.2277–9604.

Billing, K., Newland, H. and Selva, D. (2007) 'Improving patient satisfaction through information provision', *Clinical and Experimental Ophthalmology*, Vol. 35, No. 5, pp.439–447.

Chabouh, S., Hammami, S., Marcon, E. and Bouchriha, H. (2017) 'Appointment scheduling of inpatients and outpatients in a multistage integrated surgical suite: application to a Tunisian ophthalmology surgery department', *Journal of Simulation*, Vol. 12, No. 1, pp.67–75 [online] https://doi.org/10.1080/17477778.2017.1398288.

Crema, M. and Verbano, C. (2021) 'Simulation modelling and lean management in healthcare: first evidences and research agenda', *Total Quality Management and Business Excellence*, Vol. 32, Nos. 3–4, pp.448–466.

Demir, E., Southern, D., Verner, A. and Amoaku, W. (2018) 'A simulation tool for better management of retinal services', *BMC Health Services Research*, Vol. 18, No. 1, p.759 [online] https://doi.org/10.1186/s12913-018-3560-5.

Ershadi, M.M. and Shafaeizadeh, A. (2021) 'Simulation-based improvement and modification for performances of hospitals: a case study', *International Journal of Simulation and Process Modelling*, 1 January, Vol. 16, No. 2, pp.90–104 [online] https://doi.org/10.1504/IJSPM.2021.115857.

Fricks, R.B., Tseng, H., Veihl, M., Trivedi, K.S. and Barr, R.C. (2018) 'Robust prediction of treatment times in concurrent patient care', *Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, July, pp.5370–5373, DOI: 10.1109/EMBC.2018.8513569, PMID: 30441550.

Greasley, A. and Edwards J.S. (2019) 'Enhancing discrete-event simulation with big data analytics: a review', *Journal of the Operational Research Society*, Vol. 72, No. 2, pp.247–267.

Heshmat, M., Eltawil, A.B. and Abdelghany, M. (2023). 'Operations planning in outpatient chemotherapy with hybrid simulation modelling', *International Journal of Simulation and Process Modelling*, Vol. 18, No. 4, pp.296–303 [online] https://doi.org/10.1504/IJSPM.2022.128277.

Hong, T.S., Shang, P.P., Arumugam, M. and Yusuff, R.M. (2013) 'Use of simulation to solve outpatient clinic problems: a review of the literature', *South African Journal of Industrial Engineering*, Vol. 24, No. 3, pp.27–47 [online] https://doi.org/10.7166/24-3-551.

Hribar, M.R., Biermann, D., Read-Brown, S., Reznick, L., Lombardi, L., Parikh, M., Chamberlain, W., Yackel, T.R. and Chiang, M.F. (2017) 'Clinic workflow simulations using secondary EHR data', *AMIA Annu. Symp. Proc.*, 10 February, pp.647–656, PMID: 28269861; PMCID: PMC5333308.

Hribar, M.R., Read-Brown, S., Reznick, L. and Chiang, M.F. (2018) 'Evaluating and improving an outpatient clinic scheduling template using secondary electronic health record data', *AMIA Annu. Symp. Proc.*, 16 April, pp.921–929, PMID: 29854159; PMCID: PMC5977636.

Jin, X., Sivakumar, A.I. and Lim, S.Y. (2013) 'A simulation based analysis on reducing patient waiting time for consultation in an outpatient eye clinic', in *Proceedings of the 2013 Winter Simulation Conference: Simulation: Making Decisions in a Complex World*, IEEE Press, pp.2192–2203.

Joseph, A., Hijal, T., Kildea, J., Hendren, L. and Herrera, D. (2017) 'Predicting waiting times in radiation oncology using machine learning', in *2017 16th IEEE International Conference on Machine Learning and Applications (ICMLA)*, IEEE, December, pp.1024–1029 [online] https://doi.org/10.1109/ICMLA.2017.00-16.

Kern, C., König, A., Fu, D.J., Schworm, B., Wolf, A., Priglinger, S. and Kortuem, K.U. (2021) 'Big data simulations for capacity improvement in a general ophthalmology clinic', *Graefes Arch. Clin. Exp. Ophthalmol.*, May, Vol. 259, No. 5, pp.1289–1296, DOI: 10.1007/s00417-020-05040-9. Epub 2021 January 2, PMID: 33386963; PMCID: PMC8102441.

Khanna, R.C., Sabherwal S., Sil, A., Gowth, M., Dole, K., Kuyyadiyil, S. and Chase H. (2020) 'Primary eye care in India – the vision center model', *Indian Journal of Ophthalmology*, Vol. 68, No. 2, pp.333–339.

Lin, C.K.Y., Ling, T.W.C. and Yeung, W.K. (2017) 'Resource allocation and outpatient appointment scheduling using simulation optimization', *Journal of Healthcare Engineering*, p.9034737[online] https://doi.org/10.1155/2017/9034737.

Lin, W.C., Goldstein, I.H., Hribar, M.R., Sanders, D.S. and Chiang, M.F. (2020) 'Predicting wait times in pediatric ophthalmology outpatient clinic using machine learning', *AMIA Annu Symp Proc.*, 4 March, pp.1121–1128, PMID: 32308909; PMCID: PMC7153152.

Lowalekar, H. and Ravichandran, N. (2019) 'Managing operating performance at an ophthalmology clinic', *British Journal of Healthcare Management*, Vol. 25, No. 12, pp.1–13.

Luo, L., Zhou, Y., Han, B.T., Shi, Y., Song, Q., He, X. and Guo, Z. (2016) 'A simulation model for outpatient appointment scheduling with patient unpunctuality', *International Journal of Simulation and Process Modelling*, Vol. 11, Nos. 3/4, pp.281–291.

Mocarzel, B., Shelton, D., Uyan, B., Pérez, E., Jimenez, J.A. and DePagter, L. (2013) 'Modeling and simulation of patient admission services in a multi-speciality outpatient clinic', in *Proceedings of the 2013 Winter Simulation Conference: Simulation: Making Decisions in a Complex World*, IEEE Press, December, pp.2309–2319, DOI: 10.1109/WSC.2013.6721606.

Mohebbifar, R., Hasanpoor, E., Mohseni, M., Sokhanvar, M., Khosravizadeh, O. and Isfahani, H.M. (2013) 'Outpatient waiting time in health services and teaching hospitals: a case study in Iran', *Global Journal of Health Sciences*, Vol. 6, No. 1, pp.172–180.

Munavalli, J.R., Rao, S.V., Srinivasan, A. and van Merode, G.G. (2020a) 'Integral patient scheduling in outpatient clinics under demand uncertainty to minimise patient waiting times', *Health Informatics Journal*, Vol. 26, No. 1, pp.435–448 [online] https://doi.org/10.1177/1460458219832044.

Munavalli, J.R., Rao, S.V., Srinivasan, A. and van Merode, G.G. (2020b) 'An intelligent real-time scheduler for outpatient clinics: a multi-agent system model', *Health Informatics Journal*, Vol. 26, No. 4, pp.2383–2406 [online] https://doi.org/10.1177/1460458220905380.

Munavalli, J.R., Rao, S.V., Srinivasan, A., Manjunath, U. and van Merode, G.G. (2017) 'A robust predictive resource planning under demand uncertainty to improve waiting times in outpatient clinics', *Journal of Health Management*, Vol. 19, No. 4, pp.563–583 [online] https://doi.org/10.1177/0972063417727627.

Naiker, U., FitzGerald, G., Dulhunty, J.M. and Rosemann, M. (2018) 'Time to wait: a systematic review of strategies that affect out-patient waiting times', *Australian Health Review*, Vol. 42, No. 3, pp.286–293.

Norouzzadeh, S., Riebling, N., Carter, L., Conigliaro, J. and Doerfler, M.E. (2015) 'Simulation modeling to optimize healthcare delivery in an outpatient clinic', in *2015 Winter Simulation Conference (WSC)*, IEEE, December, pp.1355–1366.

Omotoye, O., Ajayi, I., Ajite, K. and Ajogbasile, O. (2017) 'Factors responsible for prolong waiting time of patients seeking eye care at a tertiary health facility', *Asian Pacific Journal of Health Sciences*, Vol. 4, No. 2, pp.224–228 [online] https://doi.org/10.21276/apjhs.2017.4.2.35.

Ordu, M., Demir, E., Tofallis, C. and Gunal, M.M. (2020) 'A novel healthcare resource allocation decision support tool: a forecasting-simulation-optimisation approach', *Journal of the Operational Research Society*, Vol. 72, No. 3, pp.485–500.

Pan, C., Zhang, D., Kon, A.W., Wai, C.S. and Ang, W.B. (2015) 'Patient flow improvement for an ophthalmic specialist outpatient clinic with aid of discrete event simulation and design of experiment', *Health Care Management Science*, Vol. 18, No. 2, pp.137–155 [online] https://doi.org/10.1007/s10729-014-9291-1.

Roy, S., Prasanna Venkatesan, S. and Goh, M. (2021) 'Healthcare services: a systematic review of patient-centric logistics issues using simulation', *Journal of the Operational Research Society*, 3 October, Vol. 72, No. 10, pp.2342–2364.

Roy, S.N., Shah, B.J. and Gajjar, H. (2020) 'Application of simulation in healthcare service operations: a review and research agenda', *ACM Transactions on Modeling and Computer Simulation (TOMACS)*, 31 December, Vol. 31, No. 1, pp.1–23.

Shoaib, M. and Ramamohan, V. (2022) 'Simulation modeling and analysis of primary health center operations', *Simulation*, Vol. 98, No. 3, pp.183–208, DOI: 10.1177/00375497211030931.

Sriram, S. and Noochpoung, R. (2018) 'Determinants of hospital waiting time for outpatient care in India: how demographic characteristics, hospital ownership, and ambulance arrival affect waiting time', *International Journal of Community Medicine and Public Health*, Vol. 5, No. 7, pp.2692–2698.

Zhu, Z., Heng, B.H. and Teow, K.L. (2012) 'Analysis of factors causing long patient waiting time and clinic overtime in outpatient clinics', *Journal of Medical System*, Vol. 36, No. 2, pp.707–713.