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A SERVICE-TIME PREDICTION MODEL IN SIMULATION OF QUEUING ANALYSIS FOR DECISION SUPPORT IN HEALTHCARE

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Abstract:
TheRadiologyDepartmentofahospitalinNajrancityinSaudiArabiaisseekingwaysto improve patient experience and use current resources more efficiently as they facegrowing visits numbers of patients. This study's identified primary key performanceindicatorsarepatient’swaitingtimeandstaff’sidletime.Theimpactonpatientwaitingtime and radiographers' idle time were explored in this study by using data miningtechniques to predict the service time. The same simulation technique is used to studythe impact of assigning a type of patients to a fast track, or separate unit for low-acuitypatientsintheRadiologyDepartmentusinganoperationalresearchqueue-basedMonteCarlo simulation in a spreadsheet-based decision support tool.The model combinedtheprinciplesofqueuingtheory.In addition,itexpandedthediscreteeventsimulationinorderto account for patients' arrival time rate and service time. In addition, the Departmentqueuesystemwasdesignedandanalyzedbyusingthesimulationmodel.Thepredictionmodel has been deployed into the decision support tool. Developing this tool aims toanalyzetheeffectofchangingparticularaspectsofthesystemonthetotalwaitingtime.Thesimulationindicatesthatthemainproblemisnottheshortageofresources,butitisineffective queue system management. Simulation results exhibited that the ability toaccurately predict the service time and assign patients to a particular type of scanningroom like a fast track minimized overall average waiting times 48.6 minutes to 40.4minutes in the department during operation hours. This modeling approach with adecision support tool could be efficiently distributed and inform healthcare decision-makersof implementingafasttrack orcomparablesystem onpatients' waitingtimes.

Keywords: Service-Time Prediction, Simulation of Queuing Analysis, Decision Support, Healthcare.

Background:

With continuous population growth, access to medical care is in extreme demand, andqueues are becoming longer. Although there is an elevated inauguration of advancedtechnologies to upgrade service thrift, the quality of care providedisremarkablyaffectedbyhighpatientwaittimesinthecurrentage.ThehealthsectorinTheKingdomof Saudi Arabia is no exception. Where the Saudi Health sector continues to recordincreased numbers of people visiting hospitals. The increasing pressure on healthcarefacilitiesfromtherisingnumberofpatientshasaffectedthequalityofservicesandthepatients's atisfaction(Al-Damen2017).However,thelimitedfinancialandnonfinancialresources are inadequate to cater to the high numbers of patients seeking medicalattention.Thehospitalsnotedthattheincreaseinarrivalpatientscontributestoinefficiencies, including prolonged waiting times and health services. For example,patientshavetowaitlongerinpharmacy,laboratory,physiology,andespeciallyradiologydepartments.

Thedelaysincaremayleadtoincreasedpatientcomplaints/inconveniencesanda spike in mortality rates, especially those seeking emergency treatment. In addition, patientsareforcedtoqueueinhallways,whichcreatescongestionandmayencouragethespreadof airborne diseases. Some of the patients may walk away from the hospital because ofthe delays in providing services or avoid seeking medical attention whenever they fall.The negative perceptions about the quality of services provided can exacerbate healthrisksdueto thereluctanceof individuals to go to thehospitals.

This chapter represents the introduction of this dissertation, which provides ageneral view of this study, including the background and motivation, the problemstatement,theresearchquestions,theresearchobjectives,andthescopeofthisdissertation.

ProblemStatement:

The study problemcanbeconsideredasoneoftheperplexingmanagementproblems in the hospital. The management requires a data-driven approach to improvethe queue system based on a new strategy. This project will study the strategy. Theinitial plan of this project is to propose a method with two phases. The first phasepredictsthepatientservicetimebasedontheavailabledata.Themaingoalistoclassifypatients according to their procedure durations. Reliable patient service times lead tobetter queue management. The author aims to maximize the RD utilization and reducethe patients'waitingtime andthe radiographers' overtime.The rightdata mining(machinelearning)methodsareunknownandremainaresearchquestion.Therightdatamodel also needs to be extracted from medical data. The prediction algorithm shouldbeveryaccurateinordertoleadtoeffectivequeuemanagementandpatientassignmentproblem. The second phase uses the predictive model to simulate its impact on thewaitingtimeand otherimportant metrics.

The current work is one of the pioneer projects designed to utilize simulationmethodsanddataminingtoimprovepatientqueuemanagementinhealthcarefacilities.Aftersometime,itmaybenecessaryforthehospitalstoassessitseffectivenessinqueuemanagement in the radiology department. For complex cases, a new/ additional roomwas proposed in the RD to reduce waiting times. The current study supports the use oftheEmergencySeverityIndex(ESI)inpatientschedulingintheRD.TheESIcanallowradiologists to serve patients with severe conditions in a different room from those thatrequire faster and more straightforward procedures (Al-Damen 2017). Although theapproachesusedinemergencydepartmentsareessentialfast-tracks,thereisscanty scientificevidenceconcerningtheappropriatemethodstoevaluatetheefficacyorneedof fast-track indexing systems in the RD. At present, researchers can only estimate theimpactof fast-track systems in the RD.

Anotherissueistheoperationalmanagementruleoftheproposedqueuesystem.Generally, there are RD patients who arrive too early before their appointment times.In the case they are late, the radiographers stay idle until a patient is ready. Therefore,how to deal with the patients who come either too early or too late? Important to notethatthechoiceofstrategyaffectsthewaitingtimeandradiographers'overtime.Howtoaddressthis issue is partof theresearch?

ResearchQuestions:

Thisdissertationisconcernedwithproposinganeffectivedecisionsupporttoolthatcanaddress the queue problem based on simulation and machine learning techniques.Therefore, the dissertation’s basic concern is to answer the following main researchquestion:

Howtodevelopaqueue modelthatreduce waitingtimeeffectively?

Endeavoring to answer the above research question, several sub-researchquestions come to the fore. Answering these sub-research questions will provide uswitha morecomprehensiveand moreaccurateanswer tothemain question:

- How to model the current queuing situation in the RD?
- How to improve the current queuing performance in the RD?
- What machine learning method produces the lowest error rate in predicting service time?
- How to integrate the queue model with the simulation model (Monte Carlo) and predictive model?

ResearchObjectives:

The main goal of this dissertation is to develop a spreadsheet-based model-drivendecision support tool that manipulates a predictive model and simulation models.Thisgoal will be achieved via conducting several modeling and programming activities. Toachievethis objective, thefollowing sub-objectives areidentified:

1. To propose a new queue model for the Radiology Department that reducespatientwaiting time.
2. Todeveloptheservicetimepredictionmodel.
3. To develop a Monte Carlo simulation model based on the queuing theory.

LiteratureReview:

Healthcare operations in recent years have been data-intensive due to the advancement of healthcare informatics in the era of the 4th Industrial Revolution. The application of health information in the healthcare system has been highly embraced based on its contribution to making effective decisions for quality improvement (Cresswell et al. 2012). The need to include healthcare informatics in the healthcare system increased with an increased need to change the fundamental structural operations in service providence. However, the introduction of technologies in different procedures can be overly expensive, which calls for applying a practical problem identification and decision-making process.

The decision-making process in the healthcare system can be divided into five distinct phases, problem finding, problem representation, data searching, the development of solutions, and evaluation of the solutions developed. Considerably the queuing and simulation model has been deemed important in evaluating healthcare systems to identify problems, as can be seen in many research work such as (Fitzagerald et al. 2017; Rema & Sikdar 2021).

Although the continuous introduction of advanced technologies in the healthcare system is valuable in improving care, providence factors such as patient waiting time and resource utilization are significant problems that healthcare organizations are facing today. Considerably, Hu et al. (2018) observe that a growing body of research has been directed towards evaluating the effectiveness of queuing theory and simulation models for patient flow in performance improvement since the last decade. The queueing and simulation models have proven to be an effective intervention in determining the relationship between patient waiting time and the utilization of available resources. Reduced patient waiting times in the radiology department by balancing demand and capacity ratios characterizes an effective performance improvement model in healthcare. Consequently, this literature review is directed towards evaluating patient flow in the radiology department through the queuing and simulation model using the Monte Carlo technique for patient flow.

Queueing theory in healthcare:
The pervading delays in the healthcare system could be solved by applying queuing models and solution strategies. Peter and Sivasamy (2019) used queuing modeling to evaluate patient waiting times and the allocation to the inner wards in the Outpatient Department (OPD). Their main objective was to assess the patient's routing process in the Outpatient Department to the inner wards. A computer simulation was used in comparing different routing policies to determine fairness and performance; the performance measures were computed under the randomized routing algorithm. Their results indicated that patients spend approximately 8-10 minutes in the service pathway. This timeframe was considered fair based on the sense that the mean arrival rates of the patients were less than the mean service rates. However, it is essential to note that the queueing model cannot determine the randomness in patient arrival rate.

Cho et al. (2017) indicated that the queuing theory could be valuable in calculating the waiting times and identifying barriers to effective consultation processes. Their study utilized the queueing approach to analyze the contribution of Electronic Medical Record (EMR) systems in reducing waiting times using digital and observational data from three hospitals. The measurement parameters for the queuing system were the average number of customers in the queue, the average number of patients in the system, the average waiting time in the queue, and the waiting time in the system. Their results indicated that the waiting times in the line and the systems reduced significantly after the introduction of the HER systems. Based on their research, it was concluded that the queueing theory could be valuable in identifying performance problems in the healthcare system.

Queueing models effectively calculate and predict different performance factors in the healthcare system based on the sense that they are simple and straightforward (Bahadori et al. 2017). The researchers utilized the queuing theory and simulation to evaluate the performance of Magnetic Resonance Imaging in the healthcare systems based on the arrival times and the average service delivery time. Excel 2013 was used in evaluating data from the queueing systems and the shifts. Their results indicated that the average time spent from the time of admission to leaving the MRI department is approximately 124 minutes, and the main problem in the hospital stemmed from the human resource. Consequently, from their study, it was concluded that the queueing theory could be instrumental in identifying and solving problems in the healthcare system.

Safdar et al. (2020) proposed the application of the Data Envelopment Analysis (DEA) Queue model in evaluating the inflow of walk-in outpatients. The researchers conducted a study on the effectiveness of the DEA model from 23rd April to 28Th May 2014. Their inputs were the wait time and length of the queue, while their outputs were the number of doctors and the consultation time. Queue monitoring was done through the Visual Basic for Applications VBA coding in Excel. Safdar et al. (2020) indicated that the DEA model is a practical approach to evaluating the inflow of walk-in patients in public hospitals. The model effectively displays the relationship between the required number of personnel, queue build-ups, and waiting time according to their results. In addition, their results indicated that patient waiting time has a noticeable contribution to the cost of a healthcare facility.

Simulation:

Simulation is a computational method for creating real-world models to understand their operation better and prepare for future advancements (Banks 1998). Simulation is recognized as a critical technology in the twenty-first century since it assists in developing systems in a range of sectors. Simulation is mainly utilized in developing and improving industrial goods (Kriegel 2015). Simulation is commonly employed as an improvement technique in many research investigations to simulate a healthcare clinical setting. A simulation model's adjustable parameters, scope, and changeable complexity are significant benefits when addressing an assignment, scheduling, or allocation problem.

The application of simulation in the healthcare system has increased dramatically in recent years. Eltwil and Abdelghany (2017) observes that simulations are computer models presented in the form of real-world systems, and they are used in the healthcare system to improve performance. The healthcare system is complex based on its dynamic nature; consequently, continuous research and experiments are deemed essential for achieving healthcare goals and objectives.

Simulation is considered necessary in the healthcare system because it can help promote constant research and experiments within a complex environment with reduced risks. Noticeably, simulation can be used in performing experiments in a limited time; the operation of lengthy procedures such as patient flow in the healthcare system can be simulated in a second.

Simulation modelling can serve different purposes in the healthcare system, especially in queuing systems. Abdelghany and Eltwil (2017) indicated that simulation modelling and analysis could be valuable in managing queuing systems since they can facilitate the development of new resource allocation policies, identifying problems in the design, information acquisition, and testing new interventions. Simulation modelling is coded to promote the evaluation of real-world systems to identify performance gaps and problems. Consequently, the tools can reduce patient waiting times in queuing systems since they provide valuable feedback that can be used in decision-making.

Simulation Software in Healthcare Domain:

Although Microsoft Excel is used extensively as a simulation in healthcare, there are other tools that can be used. Dehghanimohammadabadi and Keyser (2016) researched to illustrate the deployment of MATLAB with SIMIO as simulation software. The researchers used a multi-level verification exercise to validate and verify the effectiveness of SIMIO. Numerical assessments were performed to compare the simulation results with the expected values. Their results indicated that SIMIO is good simulation software because it contains various application programmes that can help users control an object's behavior. The programmers in SIMIO help the users to be productive based on the sense that it provides numerous possibilities to modify the desired model. Consequently, according to the authors, integrating SIMIO with a computational agent can be valuable in performing complex works such as optimization.

Borodin et al. (2018) conducted a study on the coupling of simulation by integrating two simulation tools, ARENA and CPLEX. Their research was aimed at explaining the meaning of coupling of simulation and presenting the contribution of software integration. Their results indicated that the combination of the two simulation tools is an effective method of improving the simulation potential. It helps promote a two-phase approach that includes inter-programming to identify the gaps in resource allocation and the evaluation of systems performance based on the waiting times and the patient flow. The integrating two simulation software facilitates the process of problem identification for the development through an assessment of the system from different angles. Consequently, combining the two software tools can be valuable in solving real-time problems that are complex and complicated; the tools can be used in solving problems associated with patient flow and resource allocation at the same time, therefore, increasing the chances for quality improvement. However, one challenge of this integration is that the two tools are Commercial off the Shelf (COTS), and it is challenging to integrate them.

Alternative Scenarios:

The introduction of new technologies in the healthcare system can be overly expensive. Consequently, it is vital to consider alternative scenarios for solving the identified problems before introducing new systems. The decision-making process of performance improvement is complicated since the final decision should be the ultimate solution to the identified issues. Noticeably, the most considered scenarios in the literature are resource change scenarios and process change scenarios. The resource change scenarios involve evaluating the various resources such as beds and human resources for performance improvement, while the second scenario revolves around changing procedures and policies applied in the facility.

The physical and human resources modification in the healthcare system has been associated with quality improvement. Jauregui et al. (2017) conducted research to evaluate the contribution of increasing human resources in hospitals with increased patient demand. The authors applied the waiting line models to calculate the minimum number of doctors necessary to meet current and future service demands. In addition, they used analytical models to evaluate and understand the relationship between service demand, the number of doctors, and the priority given to patients in the waiting line. Their results indicated an increase in service demand by 10% calls for having at least five doctors to ensure that the response time is about 3 minutes. Consequently, performance in hospitals is affected by the patient-doctor ratio since it affects the response time. The authors argue that when the demand for service increases by 30% without an increment in the number of doctors, patients with the lowest priority can wait up to five hours. An increment of service demand should be accompanied by an increased number of doctors since effective and quality care calls for a more significant investment of time. The results of this study are similar to that of Safdar et al. (2020), who indicated that there is an excellent relationship between the number of care providers and the waiting time. The results of Safdar et al. (2020) showed that the more the resource and service demand is imbalanced, the more patents are likely to spend in queues.

On the other hand, changing hospital processes and procedures can play a prominent role in increasing patient flow and reducing waiting times. Lewis et al. (2019) conducted research that proved that waiting times in hospitals could be reduced through appointment allocation and applying the triage model. The researchers conducted a pre-post study to collect data before introducing the process change scenarios, during the implementation, and after the execution. The process change scenario understudy was Specific Timely Appointments for Triage (STAT) and the period of study was two years. Their study indicated that the STAT method is an effective way of wait time reduction. According to the researchers, the STAT model can help reduce the wait times by up to 50% by minimizing variability. Introducing Triage intervention in the healthcare system can facilitate how patients are classified to facilitate the achievement of positive outcomes.

Predictive Modeling:

The utilization of predictive modeling in healthcare has gained much popularity in recent years. Bentayeb et al. (2019) observe that predictive modeling can help improve quality performance in healthcare systems based on its accuracy levels. With the continuous need to improve the performance of healthcare systems through the reduction of challenges such as increased waiting times, multiple constituencies in care facilities operate under the principles of predictive modeling. The healthcare system operates under exceedingly complex environments due to the unpredictable nature of its operations. Consequently, the application of predictive modeling in improving the queuing system is vital to reduce the risk asymmetry inherent in introducing new interventions. Predictive modeling contributes to the decision-making process by helping decision-makers analyze and predict the future performance of procedures and interventions before intervention. As a result, the modeling technique promotes accuracy in problem-solving in the healthcare system by reducing risk asymmetry. Noticeably, predictive modeling implements regression techniques in most cases.

However, effective modeling is built on efficient and accurate data. The effectiveness of predictive models is based on the extent to which they mimic the actual systems. Consequently, for predictive modeling to be valuable in improving the queueing system, efficient and accurate data should be collected (Bentayeb et al. 2019). In addition, the data to be used in the modeling processes should be cleansed thoroughly to reduce errors. Any error in modeling can lead to faulty observations, which affects the decision-making process. Accuracy in data collection promotes other modeling procedures such as variable creation that are deemed essential. After successful data collection, predictive modeling ends with validation and verification; this involves defining the mathematical relationship between the predictors and the predicted outcomes. The validation process in predictive modeling is considered vital to ensure that all the goals and objectives of the modeling process were achieved.

Machine Learning:

Machine learning (ML) is generally applicable when working with a large dataset to do prediction analysis or pattern identification. Medical informatics is a significant issue, and machine learning is the fastest expanding subject in computer science. The goal of machine learning is to design algorithms that can learn and evolve over time and then be used to make predictions. ML procedures are widely used in various fields, and ML prediction approaches have substantially improved the healthcare business. In addition, it enables a wide range of decision-making and alerting assistance capabilities to improve patient safety and healthcare quality. In addition, ML provides a rich set of implements, methods, and frameworks (Nithya& Ilango 2017)

Kuatbayeva et al. (2022) observe that machine learning algorithms promote predicting accuracy facilitating how desirable decisions are made from big data sets. As mentioned earlier, the development of solutions in a queueing system involves collecting and combining big data sets that can help understand operations, possible problems, and gaps affecting performance. For that, it is essential to apply practical tools that can facilitate decision-making based on logical and mathematical views. Noticeably, many popular machine learning algorithms can be applied in healthcare. For example, support vector machine and random tree.

Flow in Healthcare Process:

Flow in the healthcare process has been ruled out as one of the main factors increasing the prevalence of queuing in the system. Patient flow can lead to overcrowding and reduced quality of care, leading to recurring visits. Harron (2019) identified that patient flow in the healthcare system is affected by factors such as lack of directions and inadequate resources. There are three fundamental factors considered when determining the effects of flow in the healthcare system. The first factor is patient scheduling and admission, the second is the distribution of resources, and the third is flow schemes. Patient scheduling is based on the time taken during admissions; this covers the period taken during the appointments. Proper allocation of resources and the promotion of optimum patient routing are associated with the reduction of the average waiting time. This section will discuss flow in the healthcare process based on patient flow and patient waiting time.

Patient flow can affect patients' satisfaction levels and the quality of care provided. Oliveira et al. (2018) conducted a study to evaluate the impact of patient flow physician coordinator (PFPC) on the number of patients served within the triage limits. The researchers applied a retrospective cohort study to determine the period spent by patients before consultation and the number of individuals who left without consultation. Their study indicated that the absence of PFPC increases the waiting times resulting in an increment in the number of individuals leaving the hospital without consultation. According to their research, the presence of a PFPC can lead to a 14.8% increase in the number of individuals served within the time limits provided by the triage schedules. In addition, the study indicated that patient flow is enhanced by a collaboration between the physicians and triage nurses. Collaboration reduces the average waiting times.

On the other hand, patient waiting time refers to the time taken by patients before they receive their first consultation with a healthcare provider. Aeenparast et al. (2019) conducted a cross-sectional study to determine the effects of patients' and physicians' punctuality on the waiting time. Their results indicated that the healthcare system had applied effective interventions to reduce waiting time; the problem is accelerated by patients' and physicians' ability to maintain punctuality. In their study, 98.5 % of patients were late for their appointments, exposing them to the susceptibility of suffering from prolonged waiting time. In addition, according to the authors, the waiting time is increased by the kind of services provided by physicians. Their results indicated that about 82.6% of physicians report to work later than 8.00 AM, increasing the risk of overcrowding.

ResearchMethodology:

The methodology adopted in this study is designed for developing a decision support tool using "discrete event simulation" based on the Monte Carlo technique. Discrete Event Simulation is widely employed in research on account of the fact that it helps decision-makers test the efficacy of a system based on uncertain circumstances and behaviors. The concept behind the simulation method is analyzing and probing distinct processes in an extremely complex and uncertain environment. Consequently, the discrete event simulation is widely employed in places such as the healthcare system that is complex because the operating systems are uncertain and unpredictable. Simulation has proven to be effective in developing models that can improve the queuing system in many places, especially the healthcare system, where a maximal variability is inherent to the patients' arrival time and processing rate (Shakoor et al. 2021). Moreover, its flexibility allows for a trial of multiple cost-free alternatives or to design new workflow methodologies that could improve the behavior of an entire system without altering its existing physical form. It can also assist in forecasting resource allocation (staffing) for the multiple interactive activities and serve as an added support for decision-makers in achieving their objectives.

System Observation Data Collection:

Consolidating multiple entries is accounted for in reducing data size, i.e., if a patient undergoes five MRI procedures, then the patient would end up having five records. To prevent this, these five records are combined into one by factoring in the minimum start-time and the maximum end-time, grouped by patient name, date of visit, and procedure type. Moreover, the gathered data in the RIS excludes some detailed data on the processes such as staff-patient interaction and staff idle/waste time. The data is collected manually by observing patients in the RD and by interviewing the head of this department. Finally, the data has been cross-checked to minimize the data collection errors. From this data, several KPIs are extracted. Below is a brief list of each:

- Patient inter-arrival time
- Procedure service time

The time between arrivals is the kick-starter of every queue model. In the actual system, the cycle starts when a patient arrives at the hospital. In the model, however, it is the "start" node that injects the patients into the system following a pre-set inter-arrival time that defines the rate at which these patients arrive at the hospital. After studying the daily arrival numbers of patients and separating them into time frames to emphasize peak hours of congestion through a table, Similar arrival numbers are grouped under the same time epoch.

On observation, with the findings of very close mean and Median values, the averages can be confidently considered as means for a Poisson distribution and inputted into Microsoft Excel scheduler as arrival rates. The Poisson distribution is used for the number of patients' arrival patterns per day. It is good to use because the arrivals are all random and independent of each other. These rates are deduced from arrivals exclusive to the RD. Figure 3.2 shows gross patient arrival rates per period.

All radiology procedures are digitally imported from the RIS database, cleaned, and processed with the Microsoft Excel Input Analyser in order to determine the below- mentioned service time distributions. It is important to note that a triangular distribution of a minimum of 5 minutes, a maximum of 15 minutes, and most likely 10 minutes are added to all service times as preparation time for the procedure.

Modeling:

An improvement of a queuing system is based on the development of an effective model that imitates the actual system. Consequently, it is essential to apply the principles of a queue-based Monte Carlo simulation based on the fact that they can facilitate how uncertainties and ambiguities in the system are accounted for and limited. The patient waiting time in the healthcare system is based on the smoothness or roughness of patient flow, and the challenges and activities associated with the patient flow are the core determinants of the average waiting time. Consequently, modeling should be based on understanding the patient flow to ensure that all the factors are accounted for. Data collection before the model design is considered valuable to ensure that the system is analyzed and evaluated effectively for the development of an accurate model. Consequently, the development of a valid model in this study will be based on a practical evaluation of the RD and an understanding of the system's processes and procedures. In addition, it is vital to use an application that can facilitate effective modeling. In this study, the application selected is Microsoft Excel-based because it is easy to use and accurate.

ResultsofTimeStudyDataAnalysis:

The analysis of this study was based on data from two sources, observation and data from RIS. RIS proved to be valuable in this data analysis because they provided data on historical schedules, patient demographics, and characteristic clinical information. At the same time, observation was instrumental in collecting the second data set. Consequently, data were collected through observations of the time study in the RD selected for this research.

Patient demographics and characteristics report was generated for a month (31 working days) using the RIS to get an overview of the incoming patient population of the RD from 2021-to 2022. The data set for May is used in this study because other months' data was corrupted. It is important to note that the data collected through the RIS systems shows the patient type (in-patient and out-patients) and provides an overview of the expected number of patients that the RD serves. In this study, data points were extracted from 2,869 patients, and below are the factors considered.

1. MRN (Registration Number) as a unique key attribute
2. Gender
3. Nationality
4. Order Status
5. Procedure

6. Type

7. Date of appointment

8. Registration time

9. Check-in time (Procedure start)

10. Check-out time (Procedure end)

To analyze this study's current state performance measurement, measuring the estimated incoming patient population through the RIS system is vital. Table 1 below shows that, on average, 90.77 patients were served per day by the RD and the maximum capacity that RD has served in May is 133. This figure is vital in designing the simulation. Table 2 summarizes the incoming patient population for services in May 2021 at the RD.

Table 1: average served patients

Avraage	**90.77**
Std	20.06
Min	56
Max	133

Table2:IncomingPatientPopulationinMay2021

DATE	COUNT	FRACTION
5/1/21	83	0.02893
5/2/21	89	0.031021
5/3/21	128	0.044615
5/4/21	102	0.035552
5/6/21	108	0.037644
5/7/21	56	0.019519
5/8/21	73	0.025444
5/9/21	84	0.029278
5/10/21	95	0.033113
5/11/21	78	0.027187
5/12/21	94	0.032764

5/13/21	100	0.034855
5/14/21	70	0.024399
5/15/21	73	0.025444
5/16/21	105	0.036598
5/17/21	133	0.046358
5/18/21	96	0.033461
5/19/21	128	0.044615
5/20/21	120	0.041826
5/21/21	64	0.022307
5/22/21	82	0.028581
5/23/21	59	0.020565
5/24/21	96	0.033461
5/25/21	105	0.036598
5/26/21	92	0.032067
5/27/21	99	0.034507
5/28/21	75	0.026142
5/29/21	72	0.025096
5/30/21	75	0.026142
5/31/21	89	0.031021

Ontheotherhand,itwas essentialtorecordalltheexplanatoryfacets;table3presentspatients'characteristicsintermsoftheirgender,whileFigure5.1andTable5.4present the exogenous factors such as the type of procedures within the study period(May 2021). According to table 3, the number of male patients in the departmentduring the time of the study was significantly higher than that of female patients. Thepercentage of male patients was 62.2%, while that of the females was 37.3%. At thesame time, the results of exogenous factors proved that X-ray procedures are mostdemanded in the department, followed by CT and ultrasound. MRI, MRCP, EnemaTrisapeutic water-soluble, Urethrocytogram, MRCP W/C, MR Venography CerebralVeins, and Cystogram are the least demanded. From the study, the number of patientsdemanding X-RAY in the department was 2137, which is approximately 74.48% of allthe patients in the department, while Urethrocytogram, MRCP W/C, MR VenographyCerebral Veins, and Cystogram had one patient each accounting for approximately0.01%of all the patientsin thedepartment.

Table 3:NumberofPatientsby Gender

	NumberofPatients	Fractions
MALE	1799	62.7%
FEMALE	1069	37.3%

Type of Procedures:

The time study observations of 102 patient appointments in 5 days (4th to 8th of May2021) were recorded and observed. The data collected was filtered and analyzed toevaluate the estimated patient arrival rate and patients' type of 52 procedures and twotypes of patients: out-patient and in-patients.

Once the service time study data is analyzed, we try to identify value-adding and non- value-adding factors with the corresponding process and wait times. The patient data is first compiled and collected to visually represent the processing time and wait time on a bar chart. Figure 1 shows the reports and information summarized for each room in RD. Each room can only perform a specific procedure and cannot be mixed with other procedures.

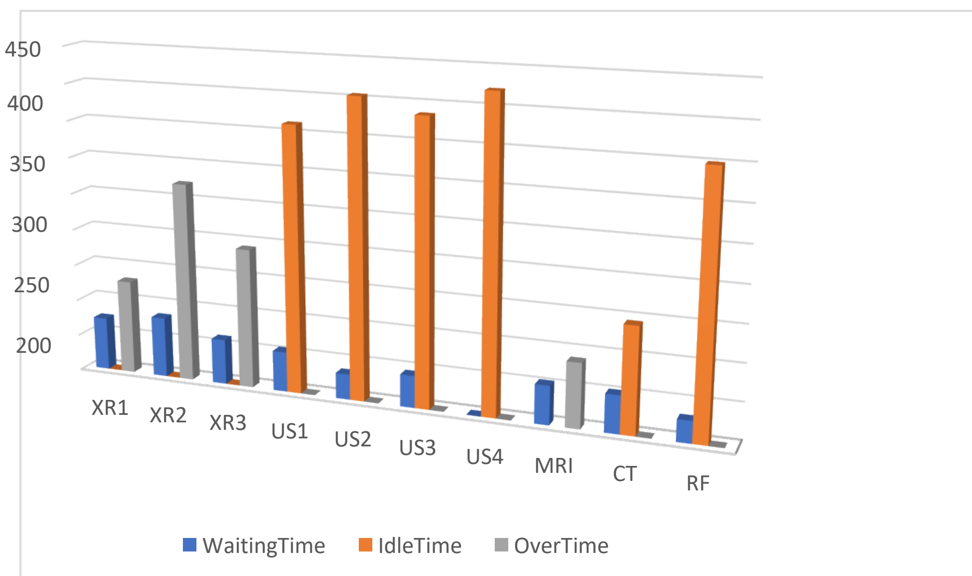

Figure1:Currentaveragewaiting time,idletime,andovertimeforallrooms

The graph shows that US4 (Ultrasound Room 4) has no waiting time by any means because the average working hours are 8 hours a day or 480 minutes a day. On the other hand, XR2 shows that over 272 minutes of overtime are used in the XR room to complete the demand for x-ray services. In addition, it is evident that the overtime issue and waiting time problem in the current systems are further caused by high idle show up. A higher idle show up leads to increased patients' wait times and the development of overtime issues. Noticeably, one of the factors leading to idle times in the department is an imbalance between the demand for services and the available resources. When the demand for services is low than the available resources, the care providers experience more idle time. This is evident from the graph where demand for ultrasound services is inferior to the available resources leading to an increase in idle time. According to the graph, the imbalance leads to the development of an average of 404 minutes of idle time a day. Noticeably, the graph shows that there is a high relationship between patient waiting times, the average over time, and the idle time experienced. The areas where a patient waits to a certain extent, more interminable over time, is developed, and high idle time can be identified; this relationship can be used to identify opportunities for improvement. In the inception of observation, we believe that these phenomena were generated by the type of queue system enforced in the RD and the problem accompanying planning. The patients were assigned into rooms and never could change their room regardless of the fact that some other rooms were idle. Box plots are used to summarize the missing data in the graphs, such as median, outlier, quartiles, and visual representation of the range. Figure 5.5 shows the box plots that represent the processing time for the RD.

ResultsforSimulationModel:

Microsoft Excel is used in developing the simulation model. Consequently, the model is designed to simulate the scanning process, representing the RD accompanying ten rooms: this section details current state analysis and optimization. The simulation was designed with the following input parameters.

1. Scheduled patient arrivals translated into arrival rates per hour .

2. Resource allocation and availability.

3. The processing time (service time) for each resource at every process station is defined by the distributions for the respective processes.

4. Patient routing is the path a patient is assigned through the system and is defined by the patient type and characteristics.

5. The simulation model's output is the Average Wait Time (AWT) and Average Idle Time (IWT) for staff.

The simulation brings about the Total Average Wait Time (AWT) for all cases, Average Wait Time (AWT) for each chamber's Idle Time, and Overtime. In addition, the simulation calculates the wait periods as a value of all the wait times a patient has experienced through the process. Table 4 demonstrates the results of the simulation alongside 250 replications. Each replication is completed for an average of 102 patients and five dominant diagnostic imaging processes. The mean waiting time is the average time for each patient waiting to be named to enter the corresponding procedure rooms. Considerably, the mean waiting times from the time study examinations are used to substantiate the simulation model. The average waiting times for each process are demonstrated in Table 4.

Table4: Comparisonbetweenobservedwaitingtimeandsimulationwaitingtime

	ObservedAverageWaitingTime (mins)	MeanSimulationAverageWaiting Times(mins)
XR 1	72.78	68.45
XR 2	82.79	80.32
XR 3	61.82	60.05
US 1	55	57
US 2	35	36
US 3	44	42
US 4	0	0
MR I	53.04	47.19
CT	51.63	65.42
RF	30	29

Duringtheobservation, thefollowingrooms were foundto beunderused.

However,theproblem wasnotserious:

- US1
- US2
- US3
- US4
- RF

As a result, while the scope of the research is to reduce the total averagewaiting time, the experiment will solely focus on reducing wait times in the followingrooms:

- XR1
- XR2
- XR3

- MRI
- CT.

Validation:

The validation of any simulation model is crucial to determine the validity of the results it brings about. Noticeably, a standard t-test helps to endorse the statistical importance of the developed current state model when in comparison to the realized result. Consequently, in this study, the T-test was performed using graphpad.com, and a summary of the results is demonstrated beneath. As the p-values equal 0.9714, the test deduces that there is no meaningful distinctness between the mean of the empirical evidence and the mean simulation process periods. The analogy between the observed data and simulation evidence is displayed in Table 5.10

P-value and statistical significance:

The two-tailed P value equals 0.9714 Confidence interval:

The mean of Observed minus Simulation equals 0.0630

95% confidence interval of this difference: From -3.7991 to 3.9251 Intermediate values used in calculations:

t = 0.0369

df = 9

Standard error of difference = 1.707

Table5:Comparisonbetweentheobserveddataandsimulationdata

Group	Observed	Simulation
Mean	48.6060	48.5430
SD	23.3626	23.1784
SEM	7.3879	7.3197
N	10	10

ServiceTimePredictiveModel:

This project found that the Support vector machine (SVM) is the best-supervisedlearning method for regression; compared to other algorithms, the SVM has the lowestrelative error rate, as shown in Figure 2. Thus, SVM is used in this project to predictservice time with a well-fitted regression model. Specifically, SVMs types used inRapidMinerhavebasedonJavaimplementationoftheSVM.Thereareusesforthis learning machine method, where can use it in regression and classification, also itprovidesafastalgorithm.AccordingtoMcGregor(2020),thelinearSVMalgorithmisbetterthansomeotheralgorithms,suchask-nearestneighbors,becausethelinearSVMalgorithmchoosesthebestlineinordertoclassifythedatapoints.Itselectsthelinethatdivides the data and is as far from the nearest data points as feasible. It is worth notingthat the SVM produces a hyperplane that distinguishes the classes as well as possible.The coefficients are represented by the weights, which are the coordinates of a vectororthogonal to the hyperplane. In other words, the output of an SVM is a kernel model,which is a function used in SVM for helping to solve the problem. In this project, thekernel modelconsistsofsevenattributes whichare:1)Nationality;2)MainProcedure; 3) Patient_Type; 4) Gender; 5) Procedure_Name, 6) Type, and 7) Age. Each of theseattributesis representedbythe following weights:

w[NATIONALITY]=34.160

w[MainProcedure]=71.792

w[PATIENT_TYPE]=6.323

w[GENDER]=46.946

w[PROCEDURE_NAME]=62.213

w[TYPE]=18.121

w[AGE]=38.103

Model	Relative Error	Standard Deviation	Gains	Total Time	Training Time (1,000 Ro...	Scoring Time (1,000 Row...
Generalized Linear Model	21.1%	± 2.2%	?	1 s	627 ms	244 ms
Deep Learning	17.9%	± 3.0%	?	878 ms	1 s	98 ms
Decision Tree	17.2%	± 3.3%	?	174 ms	20 ms	171 ms
Random Forest	15.4%	± 2.8%	?	671 ms	59 ms	317 ms
Gradient Boosted Trees	19.1%	± 3.3%	?	11 s	1 s	73 ms
Support Vector Machine	15.1%	± 3.4%	?	795 ms	69 ms	512 ms

Figure2Algorithmscomparison

In addition, in this project Weight by Correlation (WBC) operator was used.WBC calculates the attributes' relevance by computing the correlation value for eachattribute in the data set. This weighting scheme is based upon correlation, and Asattribute weight, it returns the absolute or squared value of correlation. The greater theweight of an attribute, the more important it is thought to be. Figure 3 below showsthatthemainprocedureattributehasthehighestweightat0.647.Acorrelationisa number ranging from -1 to +1 that indicates the degree of association between twoattributes. (e.g., gender and service time). A positive correlation value indicates afavorablelink.

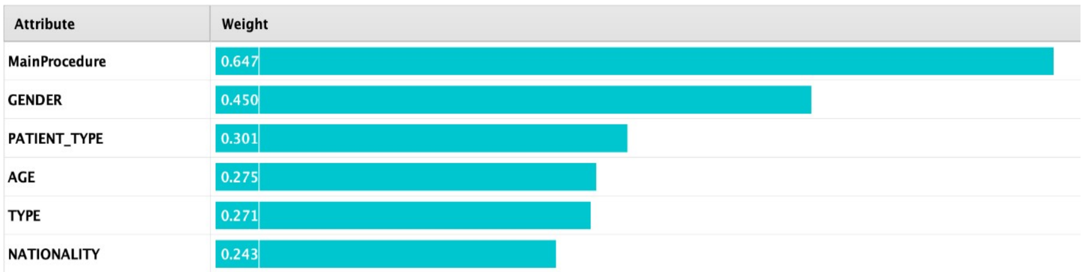

Figure3 Weights by Correlation

Kernel Model:
Total number of Support Vectors: 61 Bias (offset): 34.821

w[NATIONALITY] = 34.160

w[Main_Procedure] = 71.792

w[PATIENT_TYPE] = 6.323

w[GENDER] = 46.946

w[PROCEDURE_NAME] = 62.213

w[TYPE] = 18.121

w[AGE] = 38.103

Figure 4 shows the performance of six algorithms in terms of runtimes: generalize linear algorithm, deep learning, decision tree, random forest, gradient boosted trees, and support vector machines. The longest total runtime is (XGBOOST) at 10,876, and the DL, RF, SVM, DT, and GLM models had convergent and much shorter runtimes. The fastest is the DT which is less than 1000 ms.

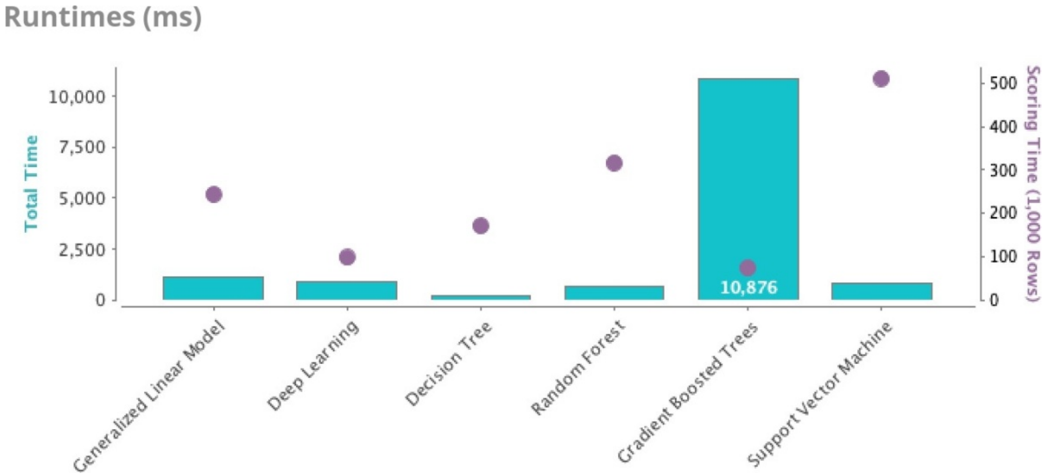

Figure4 Runtimes

Generally, the leading cause of heightened patient waiting times in healthcare facilities is ineffective service time management. Mismanagement of service times leads to the development of idle times and pressure in the RD on account of elevated demand for services; this increases the risks of overtime for healthcare providers as they try to meet the increased demands efficiently. Increased patient waiting times are provoked by factors such as getting late for scheduled appointments. When patients are late for scheduled appointments, the waiting time is heightened because the healthcare providers are forced to follow an uneven patient calling procedure. Table 5.6 shows an overview of the current arrival pattern. The data shows that 83.3% of all patients arrived in the first half of the day. The RD starts heir operation at 8 AM, alongside 60% of the patients who arrived in the first two hours. Similarly, Figure 5.1 and Table 5.7 show an overview of the patients' arrival pattern per hour in May 2021. In May 2021, it was observed that 90.5% of all patients were reported in the first half of the day, with 71.9% scheduled in the first three hours. This arrival pattern proves that the waiting time is more interminable because patients did not heed the appointment time assigned to them. The hospital grants patients to be registered even if they come too early than the assigned slots. As evident in Figure 5.2, there is a positive relationship between the reduction of service time and the patient waiting period.

Nevertheless, the reduction of service time in care delivery should be irregular since patients have distinct needs. The service times allocated to each patient should vary based on patients' needs to ensure that weighty cases are given the attention they need. However, the inauguration of new systems in the healthcare system should be based on a consideration of all the aspects that can influence the quality of services provided. Sometimes, the increase in patient waiting times is stirred by factors such as the time taken to move from one place to the other on account of the severity of the health condition. Patients with complex health conditions may need an allocation of more service time since they need more attention and take long moving from one place to another. This analogy is clear through tables 5.11 and 5.12, where the introduction of a new system and time allocation policy is only effective in some rooms. Although the XR1 and XR2 are affected positively by the new mediations, the MRI is affected negatively because the waiting times and overtime is elevated in both cases.

ResearchWorkSummary:

As the population increases, the total number of hospital visits is also increased. Statistics suggest that the growth in visits has consequences beyond the financial, which is patients' satisfaction. Hospitals are under pressure to serve an increasing number of patients with limited resources and increasing costs. Therefore, it is critical to use resources properly while caring for patients. With more patients arriving at the hospital, hospitals observe increased wait times in the imaging diagnostics or radiology department (RD). Other adverse effects include increased overtime, delay in care, and decreased patient satisfaction.

Therefore, this project was undertaken to apply a data science approach to support the hospital's management decision-making related to the long waiting service time at the Radiology Department (RD) at one of the hospitals in Saudi Arabia. Hence, this project aimed to improve patient waiting time by strengthening the appointment and queuing systems and policy management by providing a decision support tool for queue analysis. In addition, the RD management team and radiographers working at the RD were engaged in planning, implementing, and evaluating stages of the new appointment and queueing system for the RD.

In summary, this dissertation is concerned with proposing an effective decision support tool that can address the queue problem based on Monte Carlo simulation and machine learning techniques. Therefore, the dissertation's basic concern is to answer the following main research question:

How to develop a queueing model that reduces waiting time effectively?

Endeavouring to answer the above research question, several sub-research questions come to the fore. Answering these sub-research questions will provide us with a more comprehensive and more accurate answer to the main question:

I. How to model the current queuing situation in the RD?

II. How to improve the current queuing performance in the RD?

III. What machine learning method produces the lowest error rate in predicting service time?

IV. How to integrate the queue model with the simulation model (Monte Carlo) and predictive model?

In order to answer those research questions, the main goal of this dissertation is to develop a spreadsheet-based model-driven decision support tool that manipulates a predictive model and simulation models. This goal will be achieved via conducting several modeling and programming activities. To achieve this objective, the following sub-objectives are identified:

1. To propose a new queue model for the Radiology Department that reduce the patients waiting time.

2. To develop the service time prediction model.

3. To develop a Monte Carlo simulation model based on the queuing theory.

ProjectAchievementandCompletion:
In this section, the author will discuss whether the project has achieved its goal

sub-objectives and answer the research questions. Does the main research question begin with developing a queueing model that effectively reduces waiting time?

The hospital activities, plans, and processes are too complex for analytic solutions (i.e., exact methods). However, we can build a model that lets the management evaluate their plan quantitatively. The user can change the parameters and design of the queue and conduct a what-if analysis to see the results. The Monte Carlo method is effective in avoiding the 'flaw of average' in understanding the impact of a decision to the overall waiting time. Therefore, the main research question is answered by using the operational research (OR) field of queue theory. A mathematical model that represents the current state is developed using the OR methodology. Later, a simulation model technique called Monte Carlo is used to model the business flow or patient's flow in the Radiology Department of the hospital. Based on the model, a spreadsheet-based decision support tool is developed. This tool helps the author to change.

Endeavouring to answer the above research question, several sub-research questions come to the fore. We have answered all these sub-research.

I. How to model the current queuing situation in the RD? The question is answered by the research methodology.

II. How to improve the current queuing performance in the RD? The current queueing performance has been improved by implementing several innovations in the queue. One of the solutions is to add one more room for x-ray and change the queue system from multiple lines, single-phase, single server procedure to a single line, single phase but with multiple servers.

III. What machine learning method produces the lowest error rate in predicting service time? Support Vector Machine.

IV. How to integrate the queue model with the simulation model (Monte Carlo) and predictive model? The predictive model is used in the earliest part of the simulation. When a patient arrives, based on their profile to forecast the service time, the front office will then assign patients to rooms based on the service time prediction.

In order to answer those research questions, the main goal of this dissertation is to develop a spreadsheet-based model-driven decision support tool that manipulates a predictive model and simulation models. This goal will be achieved via conducting several modeling and programming activities. To achieve this objective, the following sub-objectives are identified:

a. To propose a new queue model for the Radiology Department that reduces the patients waiting time.

b. To develop the service time prediction model.

c. To develop a Monte Carlo simulation model based on the queuing theory.

Contributions:
The present study contributes to the field of health informatics and health decision support via addressing the queue management problem aiming to reduce the waiting time required to serve customers. This study ends up with an effective decision support tool which driven by a simulation model and a predictive model, together with new proposed slot-based appointment systems that can significantly reduce waiting time and overtime (cost). This was achieved by changing the appointment system from open to slot based and the development of patient assignment based on a predictive model. This proposed approach is able to take into account the type of patient and status during the triage process which not previously applied. Here follows a detail description of the contributions achieved throughout this study:

1. A new queue model for the Radiology Departments that reduces waiting time and overtime (i.e., human resource cost).

2. A new predictive model based on Support Vector Machine that is effective to predict patient's service time and segregated into special room.

3. Proposed a new appointment management based on slots of 30 minutes windows that reduces waiting time into half.

4. A spreadsheet-based model-driven decision support tool for queue analysis and planning.

LimitationofTheStudy:
The most serious problem this study encountered was data, skills set and time. This problem resulted from the following reasons:

1. The collected data from the hospital's information system contain a lot of noise, missing values and inconsistencies. Therefore, the authors are required to collect the data manually by doing observation which took a long of time to get approval. The observations were made for a month and therefore the simulation is conducted based on that particular month (May 2021).

2. All modifications of the current state which has been proposed in this study improved the waiting time, yet it added new task to the front office, which is similar to the emergency department triage and therefore, would increase workload into the existing workflow.

FutureWork:

The present study focused on developing a decision support tool to address the queueing management problem. The decision support tool is a spreadsheet model driven decision support tool that have been made on the Monte Carlo simulation technique and SVM based prediction model. The prediction model is used to predict the service time. These models succeeded in obtaining better results than those obtained by the current state. Therefore, for future works, this dissertation recommends:

1. To include optimization model based on metaheuristics algorithm for workforce planning.
2. To develop more robust algorithm to predict service time and type of patients.
3. To improve the triage policy with different effective strategy.

References:

- Abdelghany, M., & Eltawil, A. B. (2017). Linking approaches for multi-methods simulation in healthcare systems planning and management. International Journal of Industrial and Systems Engineering, 26(2), 275-290.
- Aeenparast, A., Farzadi, F., Maftoon, F., & Yahyazadeh, H. (2019). Patient flow analysis in general hospitals: How clinical disciplines affect outpatient wait times. Hospital Practices and Research, 4(4), 128-133. https://doi.org/10.15171/hpr.2019.26
- Al-Damen, R. (2017). Health care service quality and its impact on patient satisfaction “case of Al-Bashir Hospital”. https://pdfs.semanticscholar.org/effd/26b4dfca414f4bdf3c8d3998c9b050e23db 3.pdf
- Bahadori, M., Teymourzadeh, E., Hosseini, S. H., & Ravangard, R. (2017). Optimizing the performance of magnetic resonance imaging department using queuing theory and simulation. Shiraz E-Medical Journal, 18(1). https://doi.org/10.17795/semj43958
- Bentayeb, D., Lahrichi, N. and Rousseau, L.M., 2019. Patient scheduling based on a service-time prediction model: a data-driven study for a radiotherapy center. Health care management science, 22(4), pp.768-78 https://kaz2.elpub.ru/jour/article/view/19
- Borodin, V., Bourtembourg, J., Hnaien, F., & Labadie, N. (2018). COTS software integration for simulation optimization coupling: Case of ARENA and CPLEX products. International Journal of Modelling and Simulation, 39(3), 178-189. https://doi.org/10.1080/02286203.2018.1547814
- Cho, K. W., Kim, S. M., Chae, Y. M., & Song, Y. U. (2017). Application of queueing theory to the analysis of changes in outpatients' waiting times in hospitals introducing EMR. Healthcare Informatics Research, 23(1), 35. https://doi.org/10.4258/hir.2017.23.1.35
- Cresswell, K., Majeed, A., Bates, D. W., & Sheikh, A. (2013). Computerised decision support systems for healthcare professionals: an interpretative review. Journal of

Innovation in Health Informatics, 20(2), 115-128.

- Fitzgerald, K., Pelletier, L., & Reznek, M. A. (2017). A queue-based Monte Carlo analysis to support decision making for implementation of an emergency department fast track. Journal of healthcare engineering, 2017.
- Haroon, M. Z. (2019). Patient flow and waiting time in emergency Department of tertiary health care hospitals of Khyber Pakhtunkhwa. JOURNAL OF MECHANICS OF CONTINUA AND MATHEMATICAL SCIENCES, 14(6). https://doi.org/10.26782/jmcms.2019.12.00033
- Hu, X., Barnes, S., & Golden, B. (2018). Applying queueing theory to the study of emergency department operations: A survey and a discussion of comparable simulation studies. International Transactions in Operational Research, 25(1), 7-49. https://doi.org/10.1111/itor.12400
- Kriegel, J., Jehle, F., Dieck, M., & Tuttle-Weidinger, L. (2015). Optimizing patient flow in Austrian hospitals–improvement of patient-centered care by coordinating hospital-wide patient trails. International Journal of Healthcare Management, 8(2), 89-99.
- Kuatbayeva, A. A., Izteleuov, N. E., Kabdoldin, A., & Abdyzhalilova, R. (2022). Data mining models for healthcare. Advanced technologies and computer science, (3), 11-17.
- Lewis, A. K., Taylor, N. F., Carney, P. W., & Harding, K. E. (2019). Specific timely appointments for triage to reduce wait times in a medical outpatient clinic: Protocol of a pre-post study with process evaluation. BMC Health Services Research, 19(1). https://doi.org/10.1186/s12913-019-4660-6
- Nithya, B., & Ilango, V. (2017, June). Predictive analytics in health care using machine learning tools and techniques. In 2017 International Conference on Intelligent Computing and Control Systems (ICICCS) (pp. 492-499). IEEE.
- Rema, V., & Sikdar, K. (2021). Optimizing Patient Waiting Time in the Outpatient Department of a Multi-specialty Indian Hospital: The Role of Technology Adoption and Queue-Based Monte Carlo Simulation. SN Computer Science, 2(3), 1-9.
- Safdar, K. A., Emrouznejad, A., & Dey, P. K. (2020). An optimized queue management system to improve patient flow in the absence of an appointment system. International Journal of Health Care Quality Assurance, 33(7/8), 477-494. https://doi.org/10.1108/ijhcqa-03-2020-0052