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

AL QIRAD, HASHIL ALI H

PROJECT SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF HEALTH INFORMATICS

FACULTY OF INFORMATION SCIENCE AND TECHNOLOGY
UNIVERSITI KEBANGSAAN MALAYSIA
BANGI

2022

MODEL RAMALAN WAKTU PERKHIDMATAN DALAM SIMULASI ANALISIS BERGANTARA UNTUK SOKONGAN KEPUTUSAN DALAM PENJAGAAN KESIHATAN

AL QIRAD, HASHIL ALI H

PROJEK YANG DIKEMUKAKAN UNTUK MEMENUHISEBAHAGIAN DARIPADA SYARAT MEMPEROLEHI IJAZAH SARJANA INFORMATIK KESIHATAN

FAKULTI TEKNOLOGI DAN SAINS MAKLUMAT
UNIVERSITI KEBANGSAAN MALAYSIA
BANGI

2022

DECLARATION

I hereby declare that the work in this thesis is my own except for quotations and summaries which have been duly acknowledged.

1 MARCH 2022 AL QIRAD HASHIL ALI

P104387

ACKNOWLEDGEMENTS

All gratitude and praise are due to Almighty Allah for giving me the strength and capacity to complete this ultimate achievement.

I would like to express my gratitude to my country Saudi Arabia, the Saudi Ministry of Education, and the Saudi Ministry of Health for their support during my study in Malaysia.

I would like, to express my gratefulness and appreciation to my mentor Professor Mohd Zkree bin Ahmad Nazri, for his wisdom, advice, and unlimited support to complete this work. His readiness to share his valuable knowledge, time, and experience has been greatly appreciated.

I would like to gratefulness all members committee of my thesis.

I would like to thank faculty members, staff, and friends in the FTSM who had been like my family.

Finally, I would like to express my gratitude and appreciation to parents for their support and wife for being quite understanding and supportive.

ABSTRACT

The Radiology Department of a hospital in Najran city in Saudi Arabia is seeking ways to improve patient experience and use current resources more efficiently as they face growing visits numbers of patients. This study's identified primary key performance indicators are patient's waiting time and staff's idle time. The impact on patient waiting time and radiographers' idle time were explored in this study by using data mining techniques to predict the service time. The same simulation technique is used to study the impact of assigning a type of patients to a fast track, or separate unit for low-acuity patients in the Radiology Department using an operational research queue-based Monte Carlo simulation in a spreadsheet-based decision support tool. The model combined the principles of queuing theory. Also, it expanded the discrete event simulation in order to account for patients' arrival time rate and service time. In addition, the Department queue system was designed and analyzed by using the simulation model. The prediction model has been deployed into the decision support tool. Developing this tool aims to analyze the effect of changing particular aspects of the system on the total waiting time. The simulation indicates that the main problem is not the shortage of resources, but it is ineffective queue system management. Simulation results exhibited that the ability to accurately predict the service time and assign patients to a particular type of scanning room like a fast track minimized overall average waiting times 48.6 minutes to 40.4 minutes in the department during operation hours. This modeling approach with a decision support tool could be efficiently distributed and inform healthcare decision-makers of implementing a fast track or comparable system on patients' waiting times.

ABSTRAK

Jabatan Radiologi sebuah hospital di bandar Najran di Arab Saudi sedang mencari cara untuk meningkatkan pengalaman pesakit dan menggunakan sumber semasa dengan lebih cekap ketika mereka menghadapi peningkatan bilangan pesakit. Penunjuk prestasi utama utama kajian ini yang dikenal pasti ialah masa menunggu pesakit dan masa terbiar kakitangan. Kesan ke atas masa menunggu pesakit dan masa terbiar juru radiograf telah diterokai dalam kajian ini dengan menggunakan teknik perlombongan data untuk meramalkan masa perkhidmatan. Teknik simulasi yang sama digunakan untuk mengkaji kesan menugaskan jenis pesakit ke laluan pantas, atau unit berasingan untuk pesakit ketajaman rendah di Jabatan Radiologi menggunakan simulasi Monte Carlo berasaskan baris gilir penyelidikan operasi dalam sokongan keputusan berasaskan hamparan. alat. Model ini menggabungkan prinsip-prinsip teori beratur. Juga, ia mengembangkan simulasi acara diskret untuk mengambil kira kadar masa ketibaan dan masa perkhidmatan pesakit. Selain itu, sistem giliran Jabatan telah direka bentuk dan dianalisis dengan menggunakan model simulasi. Model ramalan telah digunakan ke dalam alat sokongan keputusan. Membangunkan alat ini bertujuan untuk menganalisis kesan perubahan aspek tertentu sistem pada jumlah masa menunggu. Simulasi menunjukkan bahawa masalah utama bukanlah kekurangan sumber, tetapi ia adalah pengurusan sistem baris gilir yang tidak berkesan. Keputusan simulasi menunjukkan bahawa keupayaan untuk meramalkan masa perkhidmatan dengan tepat dan menetapkan pesakit ke jenis bilik pengimbasan tertentu seperti laluan pantas meminimumkan purata masa menunggu keseluruhan 48.6 minit hingga 40.4 minit di jabatan semasa waktu operasi. Pendekatan pemodelan dengan alat sokongan keputusan ini boleh diedarkan dengan cekap dan memaklumkan pembuat keputusan penjagaan kesihatan untuk melaksanakan landasan pantas atau sistem setanding pada masa menunggu pesakit..

CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

CHAPTER I

INTRODUCTION

1.1 BACKGROUND

With continuous population growth, access to medical care is in extreme demand, and queues are becoming longer. Although there is an elevated inauguration of advanced technologies to upgrade service thrift, the quality of care provided is remarkably affected by high patient wait times in the current age. The health sector in The Kingdom of Saudi Arabia is no exception. Where the Saudi Health sector continues to record increased numbers of people visiting hospitals. The increasing pressure on healthcare facilities from the rising number of patients has impacted the quality of services and the patients' satisfaction (Al-Damen 2017). However, the limited financial and nonfinancial resources are inadequate to cater to the high numbers of patients seeking medical attention. The hospitals noted that the increase in arrival patients contributes to inefficiencies, including prolonged waiting times and health services. For example, patients have to wait longer in pharmacy, laboratory, physiology, and especially radiology departments.

The delays in care may lead to increased patient complaints/inconveniences and a spike in mortality rates, especially those seeking emergency treatment. Also, patients are forced to queue in hallways, which creates congestion and may encourage the spread of airborne diseases. Some of the patients may walk away from the hospital because of the delays in providing services or avoid seeking medical attention whenever they fall. The negative perceptions about the quality of services provided can exacerbate health risks due to the reluctance of individuals to go to the hospitals.

This chapter represents the introduction of this dissertation, which provides a general view of this study, including the background and motivation, the problem statement, the research questions, the research objectives, and the scope of this dissertation.

1.2 PROBLEM BACKGROUND

The current study is aligned to addressing one of the issues related to Health Informatics. According to Imhoff (2002), Health Informatics encompasses technologies and methods that allow professionals to collect and process patient data to improve decision-making. The data sets that may be analyzed to make healthcare decisions include medical scans, diagnostic tests, and electronic healthcare records. Patient waiting time is one of the challenges that can be addressed through computational techniques applied within the field of Health Informatics. Prolonged waiting times for patients seeking medical care is one of the main factors that lower patient satisfaction because it demonstrates a healthcare facility's weaknesses in the quality, accountability, efficiency, transparency, and delivery of services (Kuguoglu 2006; Lowe 2000; Huang 1994; Lynam 1993). Some hospitals in Saudi Arabia may likely experience up to two hours of patient waiting time before receiving treatment.

The queuing theory is paramount for understanding queuing problems, especially in healthcare settings. It allows professionals to understand the intricacies of queuing in service provision facilities, including hospitals, banks, transport, and restaurants (Cooper 1981; Gross & Harris 1985). The theory involves variables such as service rates and arrival rates that apply to any service industry. The simulations and equations deduced from the queuing theory are easy to follow and interpret. The queuing theory is crucial for estimating RD parameters in the current study, including (i) the service/procedure time and (ii) the arrival rate. The service or procedure time is the amount of time a radiologist takes to complete a scan and write a report.

The determination of arrival rate and service time considers the queue discipline, number of servers, and the probability distribution of service and interval times. The arrival process entails the distributions of lengths of time between two successive patient arrivals. The queue discipline describes the procedure followed when providing services to patients. Some of the procedures include random service, first-come-first-served, priority service, or last-come-first served. Notably, the number of servers refers to service provision points in the department. When these data are readily available, a simulation could be developed to mimic the reality with a slight difference.

Based on our observation, it is apparent that the arrival patterns of patients in a healthcare facility contribute to long patient waiting times. The appointment strategies used by a hospital influence the arrival patterns of patients. Hospitals utilize the non-block and block appointment systems. For the block system, each day is split into a certain number of slots with the same length of time. On the other hand, the non-block procedure entails appointment slots with varying lengths of time. The block appointment system is used in the radiology department. More often, patients fail to observe the allocated hospital appointment times, which forces radiologists to allow patients to seek services earlier than their scheduled appointments or later. As well, observing the block appointment slots is challenging because the service time varies from one patient to another. The failure of healthcare professionals to control the variation in service time among patients leads to more patient waiting times, staff overtime costs, and underutilization of healthcare services.

To make things worse, the appointment systems assume that patients' service times are similar. Moreover, all the medical procedures have a given average period that defines the length of the appointment interval. For that, these systems assign patients to uniform slots. In fact, the disease category and management are different from patient to patient. Patient service time is affected by several factors, so it makes sense to allow for considerable variance in these durations. In the block scheduling system, medical procedures that end earlier compensate for others that exceed the expected time. However, the inability to control service-time unpredictability results in indirect expenses such as capacity underutilization, overtime, and waiting time.

Evidence shows that the rules for organizing patient appointment sequences affect the performance and efficacy of queue systems, especially in hospitals or healthcare facilities that provide outpatient care. In one study, the authors explain the use of a data-driven system for resource allocation to enhance efficient patient scheduling and reduce waiting times (Bakker & Tsui 2017). They compare the traditional cyclic scheduling with their data-driven method in line with a hospital's resource calendar. The findings affirm that data-driven patient scheduling helps to increase hospital resource utilization and reduce service waiting times. Thus, data-driven studies are critical to support hospital decision-making processes and improve service delivery.

1.3 PROBLEM STATEMENT

The queueing problem can be considered as one of the perplexing management problems in the hospital. The management requires a data-driven approach to improve the queue system based on a new strategy. This project will study the strategy. The initial plan of this project is to propose a method with two phases. The first phase predicts the patient service time based on the available data. The main goal is to classify patients according to their procedure durations. Reliable patient service times lead to better queue management. The author aims to maximize the RD utilization and reduce the patients' waiting time and the radiographers' overtime. The right data mining (machine learning) methods are unknown and remain a research question. The right data model also needs to be extracted from medical data. The prediction algorithm should be very accurate in order to lead to effective queue management and patient assignment problem. The second phase uses the predictive model to simulate its impact on the waiting time and other important metrics.

The current work is one of the pioneer projects designed to utilize simulation methods and data mining to improve patient queue management in healthcare facilities. After some time, it may be necessary for the hospitals to assess its effectiveness in queue management in the radiology department. For complex cases, a new/ additional room was proposed in the RD to reduce waiting times. The current study supports the use of the Emergency Severity Index (ESI) inpatient scheduling in the RD. The ESI can allow radiologists to serve patients with severe conditions in a different room from those that require faster and more straightforward procedures (Al-Damen 2017). Although the approaches used in emergency departments are essential fast-tracks, there is scanty scientific evidence concerning the appropriate methods to evaluate the efficacy or need of fast-track indexing systems in the RD. At present, researchers can only estimate the impact of fast-track systems in the RD.

Another issue is the operational management rule of the proposed queue system. 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 note that the choice of strategy affects the waiting time and radiographers' overtime. How to address this issue is part of the research.

1.4 RESEARCH QUESTIONS

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

How to develop a queue model that reduce 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?

1.5 RESEARCH OBJECTIVES

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 reduces patient waiting time.
2. To develop the service time prediction model.
3. To develop a Monte Carlo simulation model based on the queuing theory.

1.6 SCOPE OF STUDY

This section outlines the scope of this study, as shown in Figure 1.1. This study falls under the definition given by Sami and Reynolds (2021) that the health informatic domain is about using computational techniques to solve problems in the health industry. This dissertation focuses on applying management science theory and predictive analytics in solving the problem. Machine learning method techniques predict service time as an input for the developed simulation model based on the Monte Carlo technique. In addition, numerous machine learning methods will be investigated to find the best model to be integrated into the solutions, such as deep learning, SVM, and decision tree. The output of this research is spreadsheet-based decision support tools which driven by the developed model. The model is based on queue theory and proposed solutions inspired by the literature review.

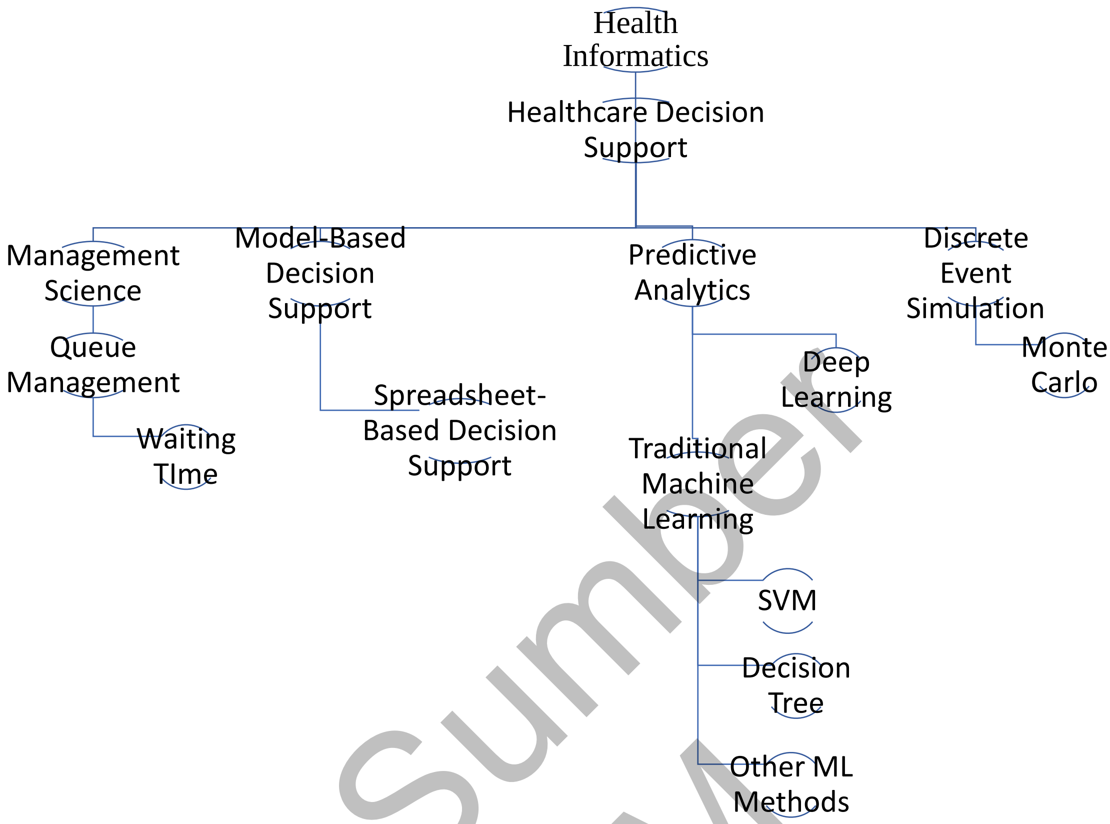


Figure 1.1. The Scope of the Study

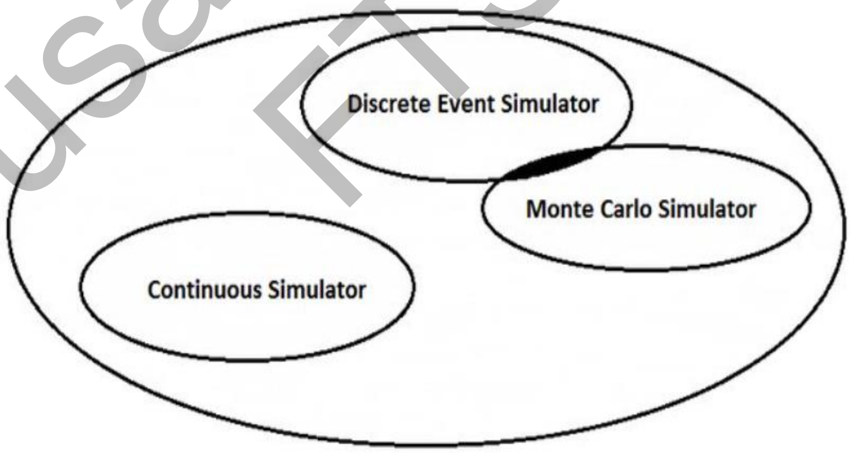


Figure 1.2. Simulations Model
(Source: http://www.cs.mun.ca/~donald/msc/node11.html)

As shown in Figure 1.2, the Monte Carlo technique is one of the discrete-event techniques for developing a simulation. The performance of the proposed models is tested using student t-test and average waiting time.

1.7 DISSERTATION OUTLINE

This dissertation includes six chapters that are organized as follows:

Chapter I represents the introduction of this dissertation which provides a general view of this study. So, the background and motivation, the problem statement, the research questions, the research objectives, and the scope of this dissertation are provided in this chapter.

Chapter II starts with a short review of the health informatics, decision support systems (DSS), and its most important extensions. After that, this chapter focuses on queueing theory, discrete event simulation, machine learning, and data mining. Predictive analytics is the focus of this dissertation, and approaches and algorithms are reported in the literature to address it. These algorithms can be categorized into exact algorithms, heuristic algorithms, and meta-heuristic algorithms (single-solution based and population-based). Furthermore, this chapter is concerned with the relationship between the Monte Carlo simulation and the predictive model.

Chapter III introduces the research methodology conducted in this dissertation. The methodology includes four major phases: System observation (i.e., problem identification) phase, modeling phase, implementation, development prescriptive model phase, development simulation model, implementation and validation, and evaluation (analysis of result). However, for each major phase, other methodologies are used to complete the research, such as. Figure 3.3 shows how Monte Carlo Simulation is developed.

Chapter IV presents a detailed explanation of the modeling outcome and how it is applied for solving the RD HRS and planning.

Chapter V clarifies and discusses how the performance of the developed Monte Carlo Based Decision Support Tool (MCB-DST) is based on the developed model reported in Chapter IV.

Finally, Chapter VI concludes the study by summarizing the findings, the contributions of the study, and recommendations for future work.

CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

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. An effective performance improvement model in healthcare is characterized by reduced patient waiting times in the radiology department by balancing demand and capacity ratios. 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.

2.2 QUEUEING THEORY

A.K Erlang introduced the queueing theory in 1913, and it was primarily applied in telephone facilities. However, today, the approach plays a prominent role in data presentation in the healthcare system using simple models. Using the queueing model in the healthcare system has played a valuable role in identifying performance problems and gaps to promote continuous improvement. Besides showing the relationship between demand and the available hospital resources, queueing models can play a valuable role in showing specialization and flexibility gaps in the facilities used in the system. The queuing modeling in the healthcare system is based on operations, designs, and analysis.

Yaduvanshi et al. (2019) conducted a study on the contribution of the queuing theory in the optimization of waiting time in the healthcare system. The study was conducted in the outpatient department of a hospital in India (Fortis Escorts Hospital), which receives long waiting times since it gets a high number of patients every day. After the problem was identified, the queuing theory was applied to help reduce delays by improving patient flows. Their results indicated that the queuing theory could be valuable in reducing the waiting times by creating a balance between the arrival rate and the service rates. In addition, the authors concluded that the queuing theory is a tool that can be used in the healthcare system to analyze complex concepts of the healthcare system for performance improvement.

2.2.1 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.

2.3 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.

2.3.1 Discrete Event Simulation

The application of DES in the healthcare system has increased dramatically in recent years. Discrete Event Simulation plays a prominent role in performance improvement because it helps in reviewing the effectiveness of existing systems. DES is widely used in the healthcare system based on its contribution to process improvement. DES is built on the assumption that systems do not change between varying events. The literature review by Vázquez-Serrano et al. (2021) indicated that DES could be used to predict the influence of patient demands and the available resources and identify the relationship between the various model variables. Consequently, the researchers identified that DES is a valuable decision-making tool in the healthcare system. The data presented by DES can be used in identifying and solving problems in existing systems through the modification of existing systems to improve performance. However, Vázquez-Serrano et al. (2021) indicated that although there is a growing body of research focused on DES, only a few papers focus on actual implementations.

Vázquez-Serrano et al. (2021) reviewed 231 papers to evaluate the contribution of DES modeling in healthcare. Their results indicated that there is an increased need to use DES in the healthcare system for different reasons. In their study, about two-thirds of the papers reviewed focused on applying DES in analytical models such as optimization. In contrast, the others were focused on applying DES in the emergency departments. Noticeably, according to their finding, the most used DES software in the healthcare system is the Arena and Simul8.

Lang et al. (2021) observed that free-event DES simulation software can be an alternative simulation tool over commercial software such as Arena and Plant simulation. Their results indicated that JaamSim is one of the best alternatives to commercial simulation software tools. However, Salabim and CloudSim can also be valuable product for DES, but it does not provide GUI for modeling, and it is only applicable to advanced users. One advantage of using a free-event DES simulation software is that it can help in reducing the cost while at the same time improving the quality of services provided to the patients. DES promotes how facilities balance resources with the patient flow to minimize healthcare costs.

2.3.2 Monte Carlo Technique

Monte Carlo simulation employs random sampling and statistical modeling to evaluate mathematical functions and simulate the processes of complicated systems. Putri et al. (2017) observes that in most cases, the queue system is a non-steady-state condition, but it can be controlled with the help of Monte Carlo simulation. The researchers conducted a queue system analysis to provide a detailed evaluation of queue models. The data used in the study were primary and secondary data, where the preliminary data was collected through observation, and the secondary data was collected through medical record installation. In addition, the Monte Carlo simulation was used in determining the effectiveness measure of the system. Their results indicated that the Monte Carlo Simulation is an effective way of solving the non-steady-state queue system. According to their result, the Monte Carlo system is effective based on the sense that it works with new trials that can be used in calculating the average waiting time in queue effectively.

The Monte Carlo simulation has different advantages, data collection, random number assignment, and model formulation and analysis, which can be combined to improve the flexibility levels. Fitgerald et al. (2016) employed the statistical functions in MATLAB to determine the relationship between current waits and service times. In addition, they used the Monte Carlo analysis for each simulation scenario. Their results indicated that the combination of Monte Carlo with MATLAB is valuable based on the sense that the simulation can be parallelized easily. In addition, they noted that the model is flexible and can be applied in different Emergency Departments.

Fitzgerald (2017) conducted a study to explore the relationship between patient wait times and nursing resource demand using the queue-based Monte Carlo simulation. Their results indicated that the modeling approach is flexible enough to be used in different aspects of the healthcare system. In addition, the model can be used in decision-making. According to the study results, the Monte Carlo simulation can be used in information hospital decisions on the fast track or the relationship between patient wait times and nursing resource demand.

2.3.3 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.

Bamporiki and Bekker (2018) researched an ongoing development of a simulation-optimization (SO) decision support system (DSS) aimed to be integrated with the Tecnomatix Plant Simulation software. The authors argue that incorporating the SO DSS program with the simulation software can help solve multi-objective optimization problems (MOO). Noticeably the simulation tool was validated using two test problems and two real-world problems, and the results were positive. The results indicated that applying the device in the healthcare system can help in improving patient flow through effective identification and mitigation of problematic aspects of variability at the various stages of patient flow. Consequently, the authors concluded that integrating a So DSS program with Tecnomatix plant simulation software can be valuable in healthcare-decision making and solving MOO problems.

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.

Brown et al. (2014) presented a Microsoft Excel tool known as the NetMetaXL necessary for performing a Bayesian network meta-analysis. The development of NetMetaXL was based on the growing need to introduce technologies that can help perform healthcare experiments with reduced risks. According to the researchers, the feature can help enhance the role of Excel in simulation based on the sense that it can be used in preparing and entering data and conducting the network meta-analysis. The tool can be used in evaluating the effects of different factors to reduce the complexity of systems. NetMetaXL can evaluate resource allocation policies and test new concepts and resources before applying. In addition, it can be used in assessing the impact of staff sizing and resource application in reducing or increasing patient waiting times. The software can be used in evaluating various scenarios to forecast the effects of lower and upper bounds of the number of care providers in a facility. Brown et al. (2014) observe that the feature is unique and instrumental based on the fact that it is user-friendly; through the tool, the results of any analysis are presented automatically in an excel spreadsheet. The feature can provide data in network diagrams, league tables, and probability plots necessary for simulation. An analysis of the tool indicated that the feature promotes the efficiency and transparency of conducting analysis through Excel; through the NetMetaXL upgraded standardization of reporting, analysis and the integration of evaluation can be done in Excel.

2.4 ALTERNATIVE SCENARIOS

As mentioned, 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. For that, the literature review in this section will be divided into two parts, the resource change scenarios and the process change scenarios.

2.4.1 Resource Change Scenarios

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.

A study by Yaduvanshi et al. (2019) indicated that poor hospital services operations cause an increased prevalence of queueing in the hospitals. According to the authors, the quality of services provided to patients is greatly determined by the staff sizing and how the human resource is distributed among different departments. In addition, the service is affected by the scheduling policies created for human resources in the facility. Research by Sibanda et al. (2017) indicated that the queueing in the radiology department is accelerated by factors such as informal and unofficial adoption of some duties. Clearly defined work schedules can play a prominent role in reducing patient waiting times. In addition, the addition of healthcare resources during peak hours can help in reducing the waiting times. Sibanda et al. (2017) opined that the reduction of overcrowding in the radiology department could only be reduced through the development of effective schedules and policies and an increment of human resources with increased demand for service. Hospitals should ensure that there is a balance between the staff sizing and demand for service ratio to promote the providence of quality services.

Singla (2020) conducted research through DES to show the contribution of Magnetic Resonance Imaging MRI in the Radiology department. The results indicated that installing MRI systems in the Radiology department promotes service providence. According to the author introducing the MRI enables the extent to which patients are treated within a reasonable average time in the system; through the resource, the waiting room time is reduced from 17 minutes to five minutes. Patient flow through the technology is increased in the sense that a higher percentage of individuals are more likely to leave the system after 120 minutes of arriving in the hospital. MRI resources facilitate the identification and mitigation of bottlenecks in patient flow. On the other hand, a study by Bahadori et al. (2017) indicated that increasing the number of beds in the Emergency Department can reduce overcrowding. In addition, the reallocation of the beds between different wards can improve patient flow, therefore, reducing the initial cost of waiting times. Consequently, the introduction of more hospital resources can facilitate the process of quality improvement.

2.4.2 Process Change Scenarios

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.

Shen and Lee (2019) indicated that triaging patients at the emergency department is one of the most effective ways of promoting operational efficiency. Their study revealed that triaging patients can lead to the reduction of approximately 34 minutes of the time spent waiting in the Emergency Department. However, for the triage to be successful, it can be accompanied by a fast track based on the sense that most patients are non-argent. Shen and Lee (2019) indicated that integrating fast track with triage can facilitate how urgent issues are dealt with. Fast track ensures that critical patients are directed to the locations with the required resources to reduce overcrowding. According to the authors, hospitals can apply a systematic registration procedure where the patients are grouped according to urgency levels; registering patients systematically ensures that resources are distributed effectively. A study by Charles et al. (2021) indicated that triage in the Emergency Department could be divided into three phases, prehospital triage, triage scene of the event, and triage upon arrival. According to the authors, prehospital triage revolves around field and disaster management. Effective waiting time management calls for the development of strategies that can facilitate how healthcare workers respond to emergencies through easy access to treatment and life-saving resources. In addition, the study by Charles et al. (2021) revealed that calculating the required service time per patient can help reduce waiting times by using prioritization schemes. After grouping patients, it is vital to understand the maximum required time for each patient to ensure that the urgent cases are prioritized.

2.5 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.

2.6 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.

2.6.1 Support Vector Machines (SVM)

Support Vector Machines (SVM) is a machine learning classifier method used in reducing classification barriers in distinct data sets. Kuatbayeva et al. (2022) conceded that SVM helps in reducing the prevalence of generalization error when classifying data sets whose pattern variables are unknown. SVM is built on structural risk mitigation models that facilitate how linear quadratic programming issues are solved. In addition, SVM facilitates the classification of non-linear and multiple data sets exposed to generalization risks. However, the effectiveness of SVM is based on the training error and the volume of machine learning.

2.6.1 Random Forest (RF)

Random Forest (RF) stems from the principles of applying decision trees to classify data sets for the development of an effective learning model. Kuatbayeva et al. (2022) opined that the success of machine learning through RF is based on the extent to which decision trees are identified and combined to reduce the complexity of big data sets. However, it is essential to note that the data sets used in RF are selected randomly from the actual data set to promote validity. About two-thirds of the data sets selected are used to develop the decision tree, while the others are used in testing the validity of the trees created. Consequently, Random Forest can be used in improving the queuing system on account of the fact that it is built on enormous uncertainties that can affect the development of practical solutions. Selecting data randomly can enhance how the risks of uncertainties are reduced through the majority voting principles of the decision trees facilitating decision-making.

2.7 METHODS COMPARISON

The healthcare system is complex because it is characterized by dynamic events that are unpredictable in most cases. Consequently, the application of sequencing algorithms in real-life events is unsuccessful in most cases. The dynamic nature of healthcare scenarios calls for the application of effective and robust interventions that can facilitate the process of patient scheduling. Interventions developed should be based on considering all the variations that can affect the quality of care provided. In addition, the intervention developed should be valuable in promoting efficacy in decision-making. Hu et al. (2018) observe that although the queueing theory is an effective model of determining problems in the healthcare system, it cannot cover all the factors affecting operations in the various departments. The queueing models reduce the complexities of hospital operations into factors such as arrival and waiting times, leading to unrealistic results. Consequently, applying the models in the RD can be challenging since it involves numerous variations and uncertainties that are sometimes unpredictable.

Nevertheless, the Discrete Event Simulation (DES) has been considered one of the most effective tools that can help in promoting efficiency in healthcare decision-making. Simulation enables how healthcare professionals' probe and analyze different scenarios of complex working environments inherent to the variables that can affect high-performance. In addition, DES is flexible since it has various alternatives that can be used in improving operations without interfering with current systems. As mentioned, the introduction of new technological resources in healthcare can be overly expensive; hence, it is vital to consider alternative resource allocations as presented by DES. Ensuring that there is a balance between service demand and available resources can be instrumental in improving performance. In addition, developing procedures that can facilitate efficient decision-making in complex situations can also be valuable. In this case, remodeling hospital procedures and introducing alternative resources can be invaluable in reducing waiting times. Interventions such as staff rescheduling and relocating resources were considered effective methods of reducing patient waiting times. Consequently, Table 2.1 summarizes the articles used in the resource change scenario. The papers are presented based on the scope of work, specific objectives, data collection method, approach, problem, tool and validation report.

Table 2.1 Summary of the Articles in Resource Change Area.

Authors	problem	Approach	Scope	Tools	Objective	Data Collection	Verification validation
Yazbeck (2018)	Queuing system	Operations Research	Radiology Department	Simulation Model	Reduce waiting time	manually and data-based	yes
Safdar et al. (2020)	Process Flow	Queueing Theory	ED	Mathematical Model	Reduce Patient Wait Time	Manually and Data-based	Yes
Yaduvanshi et al. (2019)	Queue System	Queueing Theory	Out-Patient Department	Heuristics	Reduce Patient Wait Time	Manually and Data-based	Yes
Cho et al. (2017)	EMR system	Queueing Theory	Radiology Department	Queueing Model	Reduce patient wait time & Improve decision making.	Manually and data-based	Validation
Singla (2020)	Hospital resources	Operations Research	Radiology Department	Conceptual Model	Reduce patient wait time & Improve decision making.	Manually and data-based	Yes
Bahadori et al. (2017)	Queuing system	Queuing theory	Radiology Department (MRI)	Simulation Model	Reduce patient wait time	Manually and data-based	Yes
Shen and Lee (2019)	Beds Allocation	Operations Research	Emergency department	PDSA (Plan, Do, Study, Act) cycles	Reduce patient wait time & reducing overcrowding	Manually and data-based	Yes
Yancey and O'Rourke (2021)	Queue System	Retrospective cohort study	Emergency department	Mathematical Model	Reduce patient wait time & reducing overcrowding	Manually and data-based	Yes

2.7.2 Data Collection Methods

Data collection in the healthcare system is done through two basic strategies. The first data collection strategy in healthcare is manual data collection, where data is collected from primary sources such as the radiology department. The second strategy is administrative data collection, where information is collected from the electronic systems and inpatient medical record review.

Sibanda et al. (2017) collected data using interviews, observation, and document reviews. A predetermined random sample of patients from consenting radiology departments was observed from the time of arrival to the time they left. At each stage, information about the time taken in each service and the type of equipment used was recorded. Bahadori et al. (2017) applied a cross-sectional study in the radiology department. In addition, the data was evaluated using Microsoft Excel 2013 to calculate the arrival times of patients and the time-of-service delivery based on the queuing network. Cho et al. (2017) applied the queuing theory to calculate the waiting time; their research was focused on analyzing the arrival rates and service rates before the application of EHR technology and after. In addition, the researchers applied manual data collection through patient observation. Singla (2020) applied the DES to identify the problems in care providence; the simulation method was used to determine resource utilization. Safdar et al. (2020) used the Data Envelopment Analysis (DEA) to develop a queuing model that could help evaluate patients' wait times through observation.

2.7.3 Verification and Validation

Verification of the model ensures that the implementation and modeling simulation of the conceptual model are correct and work as planned. In discrete-event models' cases, different ways can be changed to create specific random variables and review whether they deliver an outcome that has the right statistical properties or not (Murray-Smith 2015). Verification allows the model creator to identify and correct modelling flaws while also ensuring compliance with any standards and assumptions (Carson 2002).

Model validation shows that there are no substantial differences between the model and the real system and that the model accurately represents reality. There are three ways for verifying simulation data, according to Abo-Hamad and Arisha (2013): face validation, comparison testing, and hypothesis testing. Face validation is carried out by interviewing top management and nursing personnel, whereas comparison testing is carried out by comparing the outcomes of the simulation model with the system's real data. When a random sample from a population is analyzed, hypothesis testing is used. If the sample results do not support the statistical hypothesis, the hypothesis is rejected. The first and second techniques are widely employed in the field of healthcare (Abo-Hamad & Arisha 2013).

Safder et al. (2020) verified their proposed model by comparing it with previous works. The model proposed in their study is based on Microsoft Excel, used extensively in the healthcare system to improve the queue system. Cho et al. (2017) validated their model by collecting data before and after application. Collecting data after implementation was an effective method of verifying that the results collected were as expected.

2.8. 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.

2.8.1 Patient Flow

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.

Patient flow is affected by hospital-based factors such as inadequate directions. Harroon (2019) conducted a cross-sectional survey on all the tertiary hospitals of Khyber Pakhtunkhwa to study patients' progress from the time of arrival to the time they leave the hospitals. Nine hundred ten patients were selected for the study using the non-probability sampling method, and their progress from the time of arrival to the time of discharge or admission was determined. Their study indicated that patient flow is affected by factors such as insufficient resources and inadequate directions that increase the time spent from one place to the other. In their study, the medium processing time from entry to exit is approximately 60 minutes since the median waiting time for each patient is 41 minutes. The time spent moving from one place to the other is about 26 minutes.

Aeenparast et al. (2021) conducted a cross-sectional study to determine the relationship between patient flow analyses and wait times. SPSS statistical software was used to analyze data collected through workflow checklists. Their results indicated that there is a strong relationship between patient flow and wait times. According to the authors, the period spent in the hospital from the time of arrival to admission or discharge is approximately 77 minutes, without including the time spent in the pharmacies and para-clinic units. Noticeably, according to their study, over 90% of the total time is accounted for the time spent while waiting. Consequently, patient flow increases the total of time spent in the facility. In contrast, the waiting time affects patient flow, increasing the probability of more individuals leaving the facility without consultation.

2.8.2 Patient Waiting Time

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.

Zhang (2020) used a computerized based queuing theory to determine the main variables leading to increased waiting times in public hospitals. Their study indicated that increased waiting times are caused by an imbalance between the hospital resources and the amount of service demand. Their study showed that high waiting times in public hospitals are due to limited consultation rooms and doctors compared to service demand. This evidence is similar to that of Shen and Lee (2019), which indicated that an imbalance in the number of resources and the demand for service is the leading cause of increased waiting times in the healthcare system. Consequently, the problem of increased waiting time in different departments can be reduced by increasing hospital resources and introducing healthcare informatics to promote computerized decision-making.

2.9 COMPARISON

The following table will compare standard features between the papers used in table 2.2 and those used in this study. Yes, will be used to indicate that the features are the same.

Table 2.2 Summary of Compare standard Features Between the Papers

Authors	Scope	Objective	Data Collection	Verification and Validation
Aeenparast et al. (2019)	Yes	Yes	Yes	Yes
Zhang (2020)	Yes	Yes	Yes	No
Aeenparast et al. (2021)	No	Yes	No	Yes
Oliveira et al. (2018)	Yes	Yes	Yes	Yes
Harroon (2019)	Yes	Yes	Yes	No
Tlapa et al. (2020)	No	Yes	Yes	No

2.10 SUMMARY

The prevalence of waiting time in the healthcare system is one of the most severe problems facing hospitals in the healthcare system. However, the main reason why there is an increased waiting time in the healthcare system is due to an increased imbalance between the availability of resources and the increased demand for service. Consequently, the facilities can use strategies such as introducing healthcare informatics that can facilitate the decision-making process. One challenge of installing healthcare informatics is that it can be overly expensive; therefore, it is vital to identify the specific problem before buying any resource. Noticeably, healthcare facilities can use the queuing theory and Discrete Event Simulation to evaluate the efficiency of existing systems. Evaluating the systems leads to identifying the variables leading to increased waiting times and reduced patient flow from the time of arrival to the time of admission or discharge.

CHAPTER III

RESEARCH METHODOLOGY

3.1 INTRODUCTION

In this chapter, the research approach and methodologies utilized in this study are explained in detail. 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. Finally, a detailed theoretical study is investigated in the previous chapter to demonstrate the proposed methods' strength, including problem identification and challenges.

3.2 THE RESEARCH FRAMEWORK

This section will present the research framework utilized in this study. The framework of this study will be used to put the steps taken through the research. It is often used as a guide for researchers to help them narrow the scope of their study.

The research is organized into four phases. Phase 1, In phase 1, it is important to first understand the system thoroughly and define key performance indicators for the system, in addition to the decision variables that significantly impact the performance indicators. To understand the system, we observed the patients flow and the working process of the RD. Patients are shadowed through the process to observe patient-staff interactions and collect data. This data is very important in developing the simulation model later. Stakeholder interviews through phone calls and WhatsApp are conducted due to the hospital's Covid 19 Pandemic Standard Operating Procedure. Staff was interviewed to understand the process discuss satisfaction levels, patient experiences (good/bad), and patient and staff grievances with the current process. Phase one concludes with a collection of data and identified performance measures.

In phase 2, a mathematical (simulation) model is developed with the identified objective functions. The first objective function is to minimize the total patient wait-time and the second objective function is to minimize idle time and overtime. The mathematical model considers the resources required at each individual process step as the decision variables. Real-world observations are made to design and test the simulation model. The variables such as patient arrivals, service times, idle time, average waiting time, and the number of resources and process-flow data are modeled and represented in Chapter 4.

In phase 3, information derived from the observations is used to develop a simulation model. The simulation model is validated by performing a t-test. The validated simulation model is then used to leverage mathematical models by using Microsoft Excel. The computational simulation model generates solutions that satisfy all constraints of the model.

In Phase 4, analyses are performed to study the effects of changing the decision variables with the help of a main-effects plot and an interaction plot. The solutions of the simulation model are used to study the future condition-state using multiple simulations run with input parameters such as an additional resource capacity and increasing patient volume to observe the expected average patient waiting time. The experimental design, analyses, and results are discussed in Chapters 4 and 5. A summary of the research framework is shown in Figure 3.1.

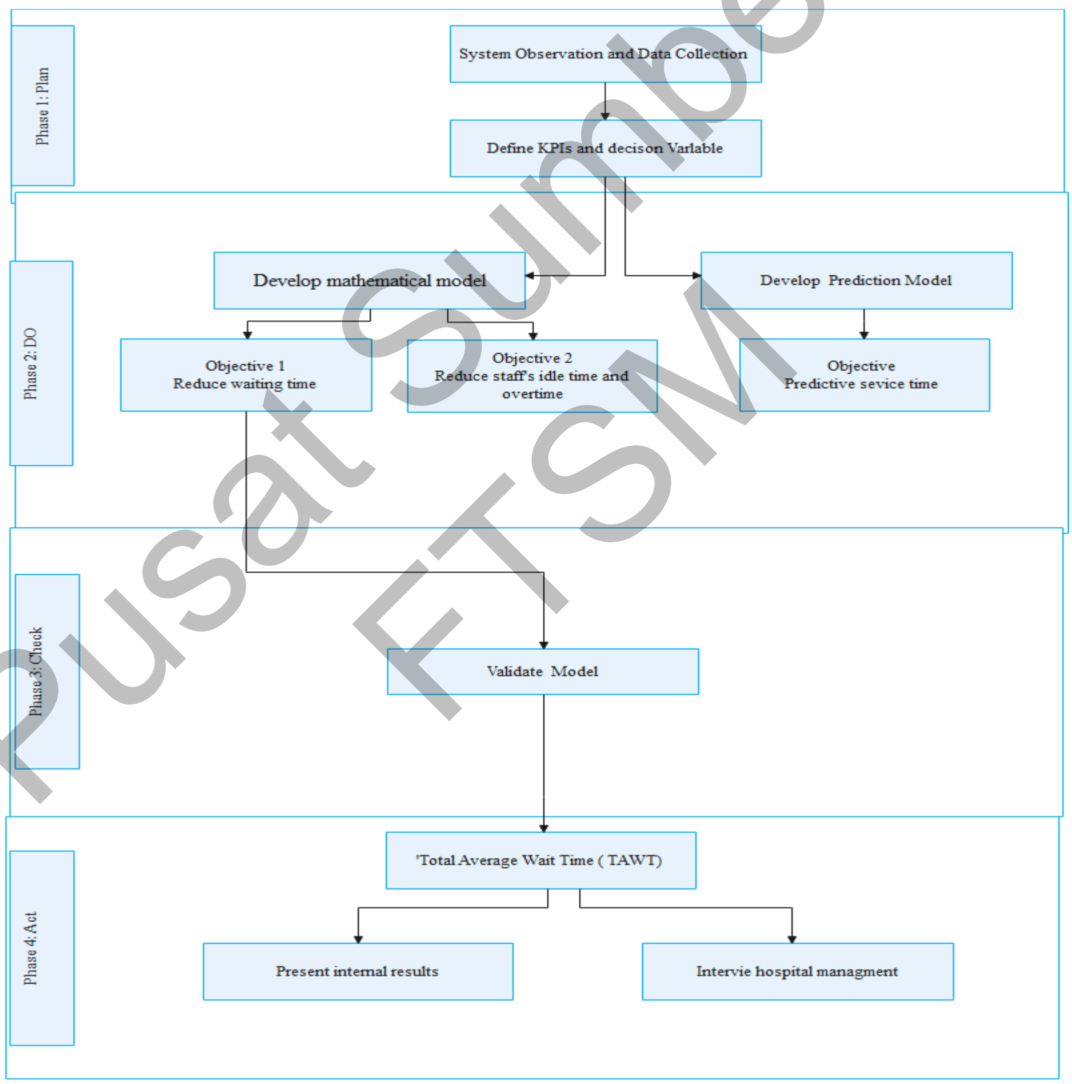


Figure 3.1 The research framework

3.3 PHASE1: SYSTEM OBSERVATION DATA COLLECTION

In this phase patients' data are collected and analyzed to define the objective function. Data collection is deemed to be a major challenge in terms of dealing with real problems. Developing a simulation model, which reflects the actual system, needs correct and sufficient data. Even with the available data, data cleaning and deriving accurate input data that can be appropriate, which reflects the actual system, need correct and sufficient data. Even with the available data, data cleaning and deriving accurate input data that can be appropriately analyzed is a demanding process.

The RD benefits from the RIS database, where the data needed for the simulation model can be extracted from. The extracted data includes patient arrival time, procedure time, and specifications on when their examinations are completed. Moreover, the gathered data in the RIS excludes some detailed data on processes such as staff-patient interaction and staff idle/waste time. However, based on the received data, the data can't be used entirely due to inconsistencies, missing values, and errors. Further, records are used only after confirming their accuracy, i.e., ensuring the removal of records in which the duration surpasses the normal range. Therefore, some of the data is collected manually by observing patients in the Radiology Department of the hospital and by interviewing the head of this department. Finally, the data is cross-checked to minimize data collection errors. Nevertheless, all big data tend to include errors, and it requires cleaning and processing before use.

Consolidating multiple entries is also 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, which are discussed in more detail in subsequent sections:

a. Patient inter-arrival time
b. Procedure service time

3.3.1 Patient Inter-Arrival 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, Table 3.1 below is populated. Similar arrival numbers are grouped under the same time epoch.

Table 3.1 Gross Patient Arrival Rate per Time Frame

	N	Min	Q_1	Median	Q_3	Max	Mean	Std Dev
7-8 AM	21	3	5	7	10	16	7.381	3.1698
8-9AM	24	2	20.75	23.5	26.25	164	26.75	30.4277
9-10 AM	24	11	60.25	78	91.25	104	70.875	29.2237
10-11AM	24	4	8.5	13.5	18.5	25	13.7917	6.6003
11-12PM	23	1	4	9	11	28	8.4783	5.9457
12-1PM	24	1	3.75	5	6	11	4.875	2.2129
1-2PM	22	1	4	4	5.75	13	4.8182	2.7192
2-3PM	23	1	3	4	6	9	4.7391	2.4903
3-4PM	19	1	2	3	3	6	2.6842	1.2933
4-5PM	16	1	1	1	2	4	1.625	0.8851

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 time frame.

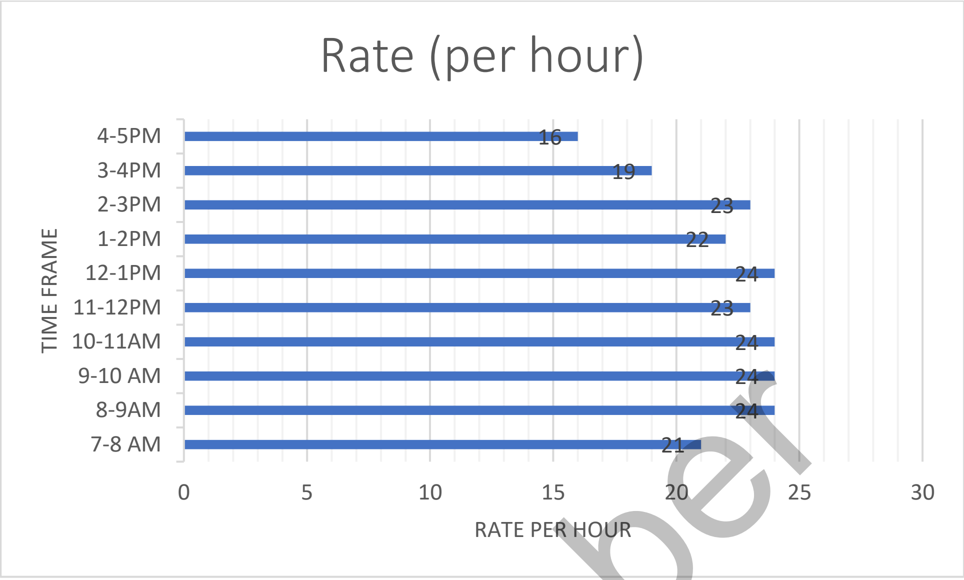


Figure 3.2- Gross Patient Arrival Rate per Time Frame Histogram

3.3.2 Procedure Service Time

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. Table 3.2 shows procedure service time distribution, these distributions are used as service time parameters in the simulation model. Also, Figure 3.3 shows the number of patients' Procedures.

Table 3.2: Procedure Service Time Distribution

Procedure	Service time Distribution	Mean	Std Deviation
CT	2.5 + EXPO(14.9)	17.4	13.2
MRI	7.5 + 54 * BETA(1.23, 1.65)	30.5	13.6
RF	NORM(32.1, 12.9)	32.1	14
US	8.5 + WEIB(20.1, 1.28)	27.1	3.32
XR	0.5 + LOGN(3.88, 4.36)	4.24	2.72

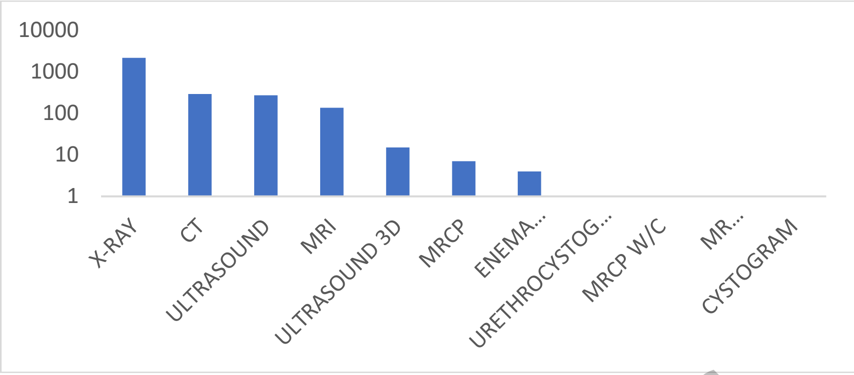


Figure 3.3- Number of patients/Procedure per Visit

3.4 PHASE 2: MODELLING

In this phase, models are designed for the RD in order to understand the RD queue system's behavior. Also, to analyze the various strategies' effectiveness and the applied scenarios in the RD. The aim is to reduce the waiting times of patients requiring radiological procedures. Something must be done about the average waiting time of more than forty-eight minutes for an imaging machine. Also, another goal is to enhance the process of decision-making in such a challenging environment. Furthermore, the simulation model examines the potential to improve patient flow in the RD in order to decrease the waiting time. Achieving this goal is likely to improve patient satisfaction.

In this phase, two types of models are developed. The first model is an analytical model, and the second model is a machine learning (predictive) model. The machine learning model is required to predict the service time of the procedure in order for the analytical model (i.e., simulation model) can be effectively function.

Based on Phase 1 observation study, the author decides that the waiting time can be further reduced if the patients can be classified by service time. A long service time patient should be assigned to a particular room. Therefore, in this phase, the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology is followed in order to develop a data mining model, or to be specific, the service time prediction model.

3.4.1 Analytical Model

In this phase, patient flow is observed, studied, and discussed throughout the system, from entering to leaving the department. After covering the path and services, the patients have to go through with their radiology procedures. A detailed study of building the model in Excel is provided (in Chapter 4) to highlight the degree of detail that is placed in the development of this model in order to make it as realistic and life-like as possible.

The analytical model or mathematical model is developed in this phase which considers the resources required at each individual process step as the decision variables. Real-world observations are made to design and test the model. The patient arrivals, processing times, number of resources, and process flow data are collected by conducting time study analyses. The last phase of this study is to evaluate and validate the simulation model by comparing the results with the actual performance. The results and discussion are explained and provided in Chapter 5.

3.4.2 Predictive Model (Machine Learning Model)

The Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology was employed in this study to develop a predictive model. Developing a predictive model is deemed important to ensure that the future effects of an intervention are evaluated before implementation. A predictive model facilitates how decision-makers implement effective interventions that can promote performance. Noticeably, the CRISP-DM is essentially a process model employing several phases that expand on the life cycle of data. Six phases establish guidelines in the planning, organization and implementation of machine learning and data science with this methodology. Figure (3.2) shows the CRISP-DM Methodology.

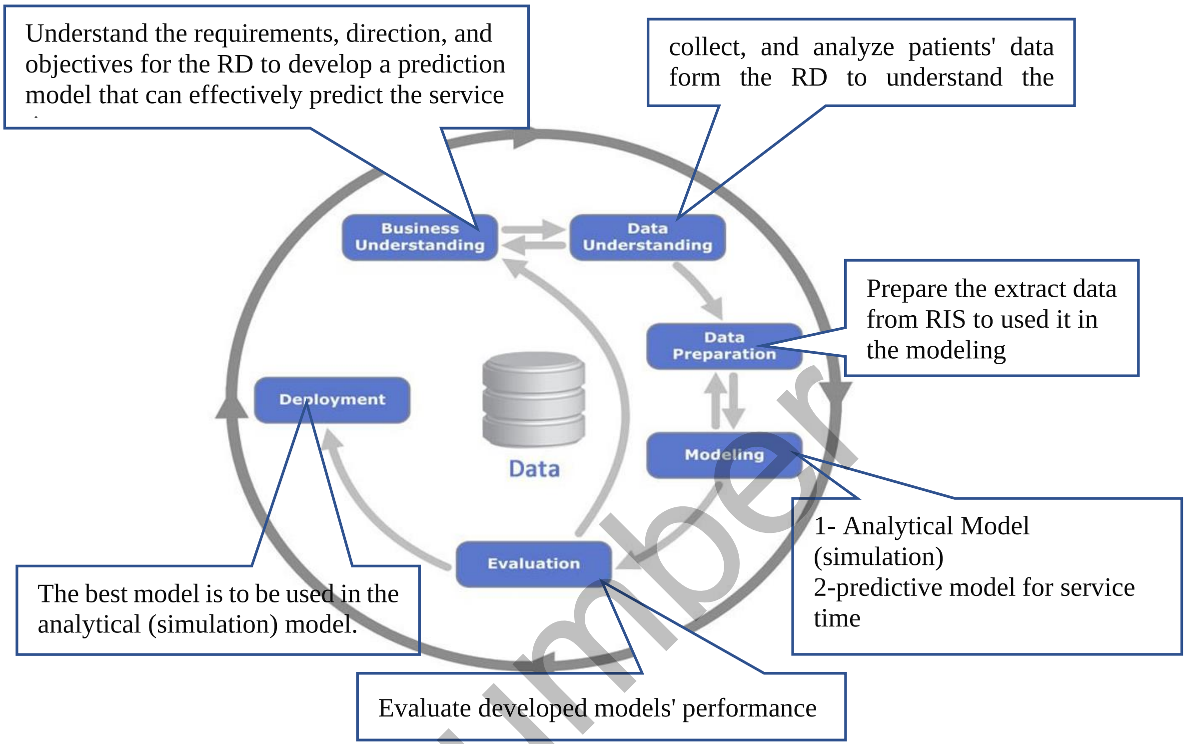


Figure 3.4 The CRISP-DM Methodology

a. Business Understanding

A key feature of the project is to understand the requirements, direction, and objectives of the business. From the problem statement of this study and a healthcare business perspective, the RD wants to improve the queue system and reduce waiting time. The business success criterion in focus is in having a shorter waiting time. The data mining goal in this project is to develop a prediction model that can effectively predict the service time of a procedure.

b. Data Understanding

This phase was aimed at driving the main goal and focus of the project by identifying, collecting, and analyzing data sets that can promote success. Consequently, this phase was completed in four tasks:

1. Collecting initial data: this involved acquiring the requisite data and loading it into an analysis tool (i.e., RapidMiner).

2. Elucidating the data: this involves tan evaluation and analysis of the data and document to understand its surface properties like the data format, number of records, or field identities.
3. Exploring the data: this step involved digging deeper into the data by querying it, visualizing it, and identifying the similarities and differences extracted from the data.
4. Verifying data quality: this involved the reduction and elimination of errors that could affect the development of an effective predictive model. In addition, it involved determining whether the document had any quality issues

c. Data Preparation "data munging."

This is where the final data set was prepared for modeling. It was completed in five steps; the following are some of these tasks:

1. Selection of data: Determine which data sets are to be used and document reasons for inclusion/exclusion.
2. Data cleaning: This was the most exhausting task in this phase since it is essential to ensure that the data selected is clear and efficient enough for modeling. Mistakes in this stage can tamper with the observation process; it can lead to the collection of erroneous observations that can affect the achievement of set goals and objectives. Consequently, adequate time was dedicated to correct, impute, and remove erroneous values.
3. Formatting the data: Re-format data as necessary.

d. Modeling

The modeling process is focused on building models and then assessing them by utilizing varied modeling methodology. This phase essentially consists of the following activities:

1. The Selection of the modeling techniques: This involves determining the possible algorithms, such as regression and neural net.

2. The Generation of test design: This task involved splitting the data into training, test, and validation sets based on the modeling approach.

3. Building the model: this involved training the model using the training data set.

4. Assess model: In most cases, the development of a model is affected by the fact that multiple models compete against each other. Consequently, it is essential to interpret the model results based on domain knowledge, the pre-defined success criteria, and the test design.

e. Evaluation

This process is focused on building and assessing various models based on several different modeling techniques. This phase essentially consists of four tasks:

1. Selection of modeling techniques: Deciding on which algorithms to apply (e.g., regression, neural net).
2. Generate test design: Pending the modeling approach, the date is split into "training," "test," and "validation" sets.
3. Build the model: Training the model using the training data set.
4. Assess the model: Typically, numerous models compete against each other. There is a necessity to explain the model outcome based on field knowledge, the predetermined success criteria, as well as the test design.

- **Mean Squared Error (MSE)**

MSE is a fundamental error metric for regression problems, and it is commonly used in predicting numeric values. In addition, the MSE is a pivotal loss function for algorithms optimization through the least-squares framing of a regression problem. In this phase, the “*least squares*” were used to represent minimizing the mean squared error between predictions and expected values.

Regression problems can be addressed with MSE as an error metric that serves as a loss function in the optimization of the use of the least-squares while framing regression problems. Noticeably, the MSE is calculated as the mean or average of the squared differences between predicted and expected target values in a dataset.

- MSE = 1 / N * sum for i to N (y_i – yhat_i)^2

Where "y_i" is the "i'th" expected value in the dataset and "yhat_i" is the "i'th" predicted value. The difference between these two values is squared, which has the effect of removing the sign, resulting in a positive error value

- **Root Mean Squared Error (RMSE)**

MSE extends with the RMSE. As suggested by its nomenclature, there is a calculation of the error's square root, thus implying that the units of the predicted target value are the same as the RMSE units. It is generally common practice to employ MSE loss in the training of predictive regression models, followed by employing RMSE for a performance evaluation.

The RMSE can be calculated as follows:

RMSE = sqrt(1 / N * sum for i to N (y_i – yhat_i)^2)

Where y_i is the i'th expected value in the dataset, yhat_i is the i'th predicted value, and sqrt() is the square root function.

We can restate the RMSE in terms of the MSE as:

RMSE = sqrt(MSE)

Note that the RMSE cannot be calculated as an average of the square root of the mean squared error values. This is a common error made by beginners and is an example of Jensen's inequality.

Note that the square root is an inverse of the square operation. MSE uses the square operation to remove the sign of each error value and to eliminate large errors. The square root reverses this operation, although it ensures that the result remains positive.

f. Deployment

A model's merit is based on its accessibility and ease of use, particularly so by the stakeholder(s) being able to access its findings. Based on the results, the best model is to be used in the analytical (simulation) model.

3.5 PHASE 3: DEVELOP AND VALIDATION OF SPREADSHEET-DSS MODEL

In this study, the methodology was embraced by many researchers such as (Adesina 2018; Cochran & Roche 2008; Cuatrecasas-Arbos 2011; Safdar et al. 2021). It primarily relies on queuing theory, simulation, and spreadsheets as the scientific foundations of the approach. Thus, these popular steps are considered, which are practiced by the scientific community in using a simple mechanism to study the system, i.e., with the use of Microsoft Excel.

The advantage of MS Excel is its ease of use and universal acceptability and applications across a plethora of industries. Not only does Excel offer simple out-of-box planning and management solutions, but it is also a tool of choice in the healthcare sector, allowing for a near real-time assessment of operations (Cochran & Roche, 2008).

The mathematical model which has been developed in Phase 2 is transformed into a computational model by using MS Excel and an application for programming (coding), specifically Visual Basic for Applications (VBA). The framework was designed in a way that it can evaluate the queue system each time a patient arrives and shows the necessary number of radiographers' 'at that moment'. A screenshot of the developed model for the radiographers is shown in Figure 3.5 and can be developed for other departments on a similar pattern. Column 'A' represents the new proposed appointment block or also known as a slot. To reduce the waiting time, we proposed that patients' appointments are based on the beginning time of a slot. Each slot is 30 minutes, and patients will not be allowed to register before the appointment time slot. In this simulation, we hide each patient's unique register number (in order to hide patient identification). Column B is used to input the slot beginning time (in minutes). The next four columns, 'C', 'D', 'E' and 'F', show the queuing data.

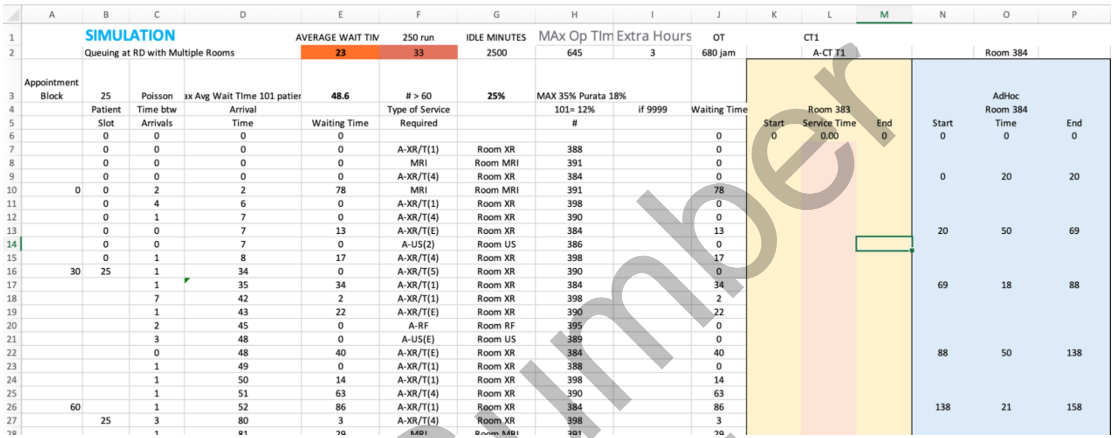


Figure 3.5. The simulation sheet

The proposed spreadsheet program consists of three main parts: the 'simulation sheet', the 'meta-data sheet' and 'look-up sheets', and lastly, the dashboard as an 'output sheet.' In addition, the program had an additional part, the graphical section, which is related directly to the simulation sheet. The function of the graph section is to present output outcomes from the output sheet as graph performance.

On the one hand, all the calculation procedures and formulae described in the earlier phase, which is explained in Chapter 4, are encoded to the meta-data sheet and look-up sheet, simulation sheet, and output sheet. On the other hand, all required data for modeling a system were processed into the meta-data sheet, indicated as waiting time sheet and service time sheet. Noticeably, these calculations were performed in the simulation sheet where the median calculations comprised facets like the mean and variability of inter-arrival time and service time for a patient at each workstation. Figures 3.6 and 3.7 show the spreadsheet model for the input and output sheets and the graph section, respectively.

26	MRI						Probability	Probability Range (Lower)	Cumulative Probability	Service Time	average	Max	496			
27	1	range2 [1.333 - 4.083]	52	0.208			0.208	0	0.208	30.28	30.00	Average	12	0.51657685	30.28	-1
28	2	range3 [4.083 - 8.200]	52	0.208			0.208	0.208	0.416	39.05	40.00			0.07813778	39.05	1
29	3	range4 [8.200 - 14.800]	52	0.208			0.208	0.416	0.624	51.95	51.63			0.90877696	51.95	-1
30	4	range1 [-∞ - 1.333]	51	0.204			0.204	0.624	0.828	50.40	51.63			0.10216822	50.40	1
31	5	range5 [14.800 - ∞]	43	0.172			0.172	0.828	1	79.92	80.00			0.26771542	79.92	1
32																
33																
34																
35	A-US(1)	57.37					Probability	Probability Range (Lower)	Cumulative Probability	Service Time	average	Max	345			
36	1	range2 [32.358 - 38.533]	15	0.20547945			0.20547945	0	0.20547945	36.02	35	Average	57.4	0.69976729	36.02	-1
37	2	range4 [43.283 - 56.842]	15	0.20547945			0.20547945	0.20547945	0.4109589	40.10	40			0.58905054	40.10	-1
38	3	range5 [56.842 - ∞]	15	0.20547945			0.20547945	0.4109589	0.61643836	48.73	49.57			0.15827116	48.73	1
39	4	range1 [-∞ - 32.358]	14	0.19178082			0.19178082	0.61643836	0.80821918	49.58	49.57			0.66433389	49.58	-1
40	5	range3 [38.533 - 43.283]	14	0.19178082			0.19178082	0.80821918	1	64.59	65			0.32724032	64.59	1
41																
42																
43	A-US(2)						Probability	Probability Range (Lower)	Cumulative Probability	Service Time	average	Max	345			
44	1	range2 [39.217 - 46.125]	15	0.20547945			0.20547945	0	0.20547945	34.23	35	Average	57.4	0.23459988	34.23	1
45	2	range4 [53.833 - 90.642]	15	0.20547945			0.20547945	0.20547945	0.4109589	39.92	40			0.25818323	39.92	1
46	3	range5 [90.642 - ∞]	15	0.20547945			0.20547945	0.4109589	0.61643836	51.35	49.57			0.73576611	51.35	-1
47	4	range1 [-∞ - 39.217]	14	0.19178082			0.19178082	0.61643836	0.80821918	49.58	49.57			0.63449917	49.58	-1
48	5	range3 [46.125 - 53.833]	14	0.19178082			0.19178082	0.80821918	1	67.58	65			0.63059182	67.58	-1
49																
50																
51	A-US(E)						Probability	Probability Range (Lower)	Cumulative Probability	Service Time	average	Max				
52	1	range2 [39.217 - 46.125]	3	0.20547945			0.20547945	0	0.20547945	33.39	35	Average		0.11020419	33.39	1
53	2	range4 [53.833 - 90.642]	3	0.20547945			0.20547945	0.20547945	0.4109589	40.48	40			0.6860303	40.48	-1
54	3	range5 [90.642 - ∞]	2	0.20547945			0.20547945	0.4109589	0.61643836	47.43	49.57			0.05021251	47.43	1
55	4	range1 [-∞ - 39.217]		0.19178082			0.19178082	0.61643836	0.80821918	49.99	49.57			0.78996332	49.99	-1
56	5	range3 [46.125 - 53.833]		0.19178082			0.19178082	0.80821918	1	65.03	65			0.68133725	65.03	-1
57																

Figure 3.6. The metadata sheet

	A-CT TE 15%	XR	A-XR/T(E)	A-XR/T(E)	A-XR/T(1)	A-XR/T(1)	A-XR/T(E)	A-XR/T(4)	A-US(2)		A-CT T(E)				
		US		A-XR/T(1)		A-XR/T(5)		A-XR/T(5)							
			Platinum			A-XR/T(4)									
Room Assigned	383	384	398	390	388	387	386	389	392	393	395	397	391	394	999
388	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
391	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0
384	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0
391	0	1	0	0	1	0	0	0	0	0	0	0	2	0	0
398	0	1	1	0	1	0	0	0	0	0	0	0	2	0	0
390	0	1	1	1	1	0	0	0	0	0	0	0	2	0	0
384	0	2	1	1	1	0	0	0	0	0	0	0	2	0	0
386	0	2	1	1	1	0	1	0	0	0	0	0	2	0	0
398	0	2	2	1	1	0	1	0	0	0	0	0	2	0	0
390	0	2	2	2	1	0	1	0	0	0	0	0	2	0	0
384	0	3	2	2	1	0	1	0	0	0	0	0	2	0	0
398	0	3	3	2	1	0	1	0	0	0	0	0	2	0	0
390	0	3	3	3	1	0	1	0	0	0	0	0	2	0	0
395	0	3	3	3	1	0	1	0	0	0	1	0	2	0	0
389	0	3	3	3	1	0	1	1	0	0	1	0	2	0	0
384	0	4	3	3	1	0	1	1	0	0	1	0	2	0	0
388	0	4	3	3	2	0	1	1	0	0	1	0	2	0	0
398	0	4	4	3	2	0	1	1	0	0	1	0	2	0	0
390	0	4	4	4	2	0	1	1	0	0	1	0	2	0	0

Figure 3.7. Meta-data of assigned rooms

3.5.2 Model Validation

When the simulation results are analyzed, the simulated outcome (average waiting time and service time) was calculated compared to the historical data output obtained from the RIS records.

The verification and validation stage are deemed vital since it helps in ensuring that the developed model is logical before proceeding to the final steps. Verification involves ascertaining that the developed model is working as expected and it can meet the objectives set. On the other hand, validation measures whether the developed model is similar to the real-world system in simulation. As mentioned, an adequate simulation model should be similar to the real-world system (Afrane & Appah 2016).

A generally used validation toleration is 10%, indicating that the output obtained from a simulation model should not be more than 10% of the actual system output. If the differences are smaller than 10%, which is within the acceptable/tolerated level of validation, a model of simulation is deemed acceptable and valid (Najmuddin et al. 2010). However, in this study, the author decided to use student T-tests to validate the developed model are not significantly different from reality. The results are discussed in Chapter 5.

3.6 PHASE 4: EVALUATION

Performance measures are the parameters that are observed to evaluate the performance and efficiency of a process. This research considers the 'Average Wait Time' (AWT) as a primary performance measure and optimizes the system by driving the AWT to a minimum. To calculate the AWT, the 'Total Wait Time' (TWT) is evaluated for every patient. The data collected from the process described in section 3.3 is used to calculate the TWT. The TWT is the sum of all intermediate wait times during a radiological procedure and is represented by equation (3.1):

$$TWT_{i,procedure} = WT_{MRI} + WT_{CT} + WT_{RF} + WT_{XR} + WT_{US} \tag{3.1}$$

Once all the TWT are calculated the AWT is calculated with the help of the following

equation:

$$AWT_{MRI} = \frac{\sum_i TWT_{procedure}}{N_{MRI}} \tag{3.2}$$

$$AWT_{CT} = \frac{\sum_i TWT_{procedure}}{N_{CT}} \tag{3.3}$$

$$AWT_{RF} = \frac{\sum_i TWT_{procedure}}{N_{RF}} \tag{3.3}$$

$$AWT_{XR} = \frac{\sum_i TWT_{procedure}}{N_{\mathrm{XR}}} \tag{3.4}$$

$$AWT_{US} = \frac{\sum_i TWT_{procedure}}{N_{\mathrm{US}}} \tag{3.5}$$

Equations (3.1) to (3.5) are represented the average waiting time for MRI, CT, RF, XR, and US, respectively.

N_{MRI}, N_{CT}, N_{RF}, N_{US}, and N_{XR} are the numbers of patient types entering the RD queue system. A new performance parameter can be defined as the 'Total Average Wait Time' (TAWT). TAWT is the sum of all the averages described above and is the most important observed parameter and allows for a high-level comparison between different scenarios. The expression for TAWT is as follows in Equation (3.6):

$$TAWT_{RD} = AWT_{MRI} + AWT_{CT} + AWT_{RF} + AWT_{XR} + AWT_{US} \tag{3.6}$$

Two ways were used to validate the case results. The first way was to present the internal results from the data sets. The second way is an interviews series of interviews with hospital management are maintained. The meetings include the staff of the RD, representing the stakeholders and decision-makers in the hospital. The results for this phase will discuss and show in Chapter 5 Table 5.11.

3.7 SUMMARY

Data collection in simulation modeling is one of the most challenging and time-consuming activities, but it is essential. Any simulation model developed to improve the queueing system should be based on accurate and efficient data to ensure that it imitates the actual system. Consequently, effective data collection methods should be applied, and effective cleansing should be done to reduce data collection errors.

In addition, it is vital to engage factors such as the DES to ensure that all the problems in the system are identified. DES is also valuable in predicting future occurrences that may affect the system's performance. Consequently, the DES can facilitate how the set objectives are achieved through an identification of the key performance indicators and the factors that affect them. The key performance indicators in this chapter were patient waiting time and physicians' idle time. Consequently, the goal was to develop a model that can facilitate the redaction of patient waiting time and physicians' idle time in the Radiology Department. Noticeably, the model was created and validated after an effective data collection process and testing that confirmed that the study's objectives were achieved. The model was validated using the student T-test to validate the developed model is not significantly different from reality.

CHAPTER IV

MODELING

4.1 INTRODUCTION

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.

4.2 AN OPERATIONAL RESEARCH (OR) -BASED QUEUE MODEL

This section will discuss the development of Operational Research (OR) based queue model in the Radiology Department (RD) using a queue-based Monte Carlo simulation method. It is important to note that the model developed was based on observation guided by queueing theory principles. The patient flow model is important to guide the development of the discrete event simulation (i.e., Monte Carlo simulation) to account for the based-time arrival rate.

4.2.1 Setting and Data Sources

The case size of this study was one hospital of the hospitals in Saudi Arabia, with over 3000 employees and 200 licensed beds. The hospital serves over 100,000 patients per year. The simulation model has been built to model the RD. We received de-identified data from the Radiology Information System (RIS), observations conducted, and management tool, including significant time- stamps for all patients during their visit. Relevant timestamps included time of arrival, arrival time in the rooms, and time-release. In addition, we banned duplicate records and records that did not include arrival and release times during data abstraction and validation. These exclusions accounted for smaller than 1% of received data.

4.2.2 Model Design

Before designing the model, we used Microsoft Excel to perform descriptive statistics on patient information to determine the average arrival rates per hour of the day. In addition, in addition, the distribution of current wait time and service time was collected.

Integrating the principles and facets of discrete event simulation (DES) in the model was necessary to promote accuracy. In addition, using DES promoted the extent to which the model represented the variations of the actual RD system. On the other hand, the model was designed in Microsoft Excel because of the programming language's ease of vector and matrix operations, easy data importation/exportation tools, and native support of mathematical functions. However, it is essential to note that the model can be developed using different programming languages because of the discrete nature of the queueing model.

a. Description of Radiology Department (RD)

The prominent role of the RD at the hospital is to provide radiological procedures to patients. Exams and procedures are performed on inpatients, emergency patients, and outpatients in neonatal, pediatric, adolescent, adult, and geriatric patient age groups. The radiology department currently offers medical services, including X-ray (XR), computed tomography (CT), ultrasound (US), fluoroscopy (RF), and magnetic resonance imaging (MRI). Each modality holds a certain number of working machines, see Table (4.1). The department has three 8-hour shifts every day, seven days a week, 365 days a year. In the RD regular, the first shift starts at 8:00 and ends at 17:00. There are dedicated machines for emergency cases under each modality see Table (4.1), which work for 24 hours every week.

Table 4.1: Number of the working machine

MODALITY	NORMAL PATIENT	EMERGENCY PATIENTS
CT	1	0
ULTRASOUND	3	1
MR	1	0
X-RAY	2	1
RF	1	0

The department process starts at the front desk through appointment requests. Consequently, the front desk in the department is aimed at ensuring that all the appointments are documented and organized for the day. Appointments are booked based on slots where the operator at the reception of the department schedules the appointments for inpatients and outpatients based on the order of slots; however, the schedule is developed with the condition that the patient is available at the given time.

However, it is essential to note that appointment requests in the RD differ based on the kind of patients. The patient himself performs requests for outpatients, and the specialty performs requests for emergencies or inpatients. At the appointment time, outpatients arrive at the desk and wait for the examination. Occasionally these patients obtain a higher priority than other patients when they are already in the hospital and require further examinations.

Regarding the inpatients, the operators plan the schedule and decide on the appointment time; however, these schedules are fixed since they are not necessarily the patient's access to services. Furthermore, inpatients are only served once the radiology department has a free slot; providers notify the referral department when a slot becomes available so that the inpatient may arrive. Unfortunately, this policy and procedure sometimes lead to increased waiting time because the referring department cannot predict when the nurse and porter will be available to transfer the patient. So, it is due to delays at the referring and the RD. Therefore, the highest priority is for emergency patients, then outpatients requiring an additional examination, inpatients, and the least priority for other outpatients.

After the patient reaches, the radiographers invite the patient for the radiological scanning and prepare (change clothes, positioning, etc.), and the examination follows. Afterward, the sub-process reporting by the radiologist observes. Finally, the radiographers send the findings to the radiologist, who analyses the results.

The following section will discuss patients' flow throughout the Radiology Department system, from entering the radiology department to leaving it. After covering the track and services, the patients have to take to go through with their radiology procedures, a detailed study of building the model will be given to highlight the degree of detail that was put into the development of this model to make it as realistic as possible.

4.2.3 The Patient’s Flow

The patient flow can be referred to as the path that patients take from the time of arrival to the time of exit in the facility. Patient flow in the radiology department is a combination of the events and procedures that patients go through between entrance and exit; this involves activities such as imaging, physician assessments, and procedures in the allocated unit. Consequently, it is vital to evaluate patient flow because it plays a prominent role in determining the average waiting time. Patient flow is affected and influenced by factors such as resource allocation and the policies promoted; these factors are significant contributors to increased waiting time in the healthcare system. On the other hand, patient flow influences the planning and management of the queuing system; it controls how resources are allocated and utilized and the policies developed and implemented. Figure 4.1 shows patient flow at the RD.

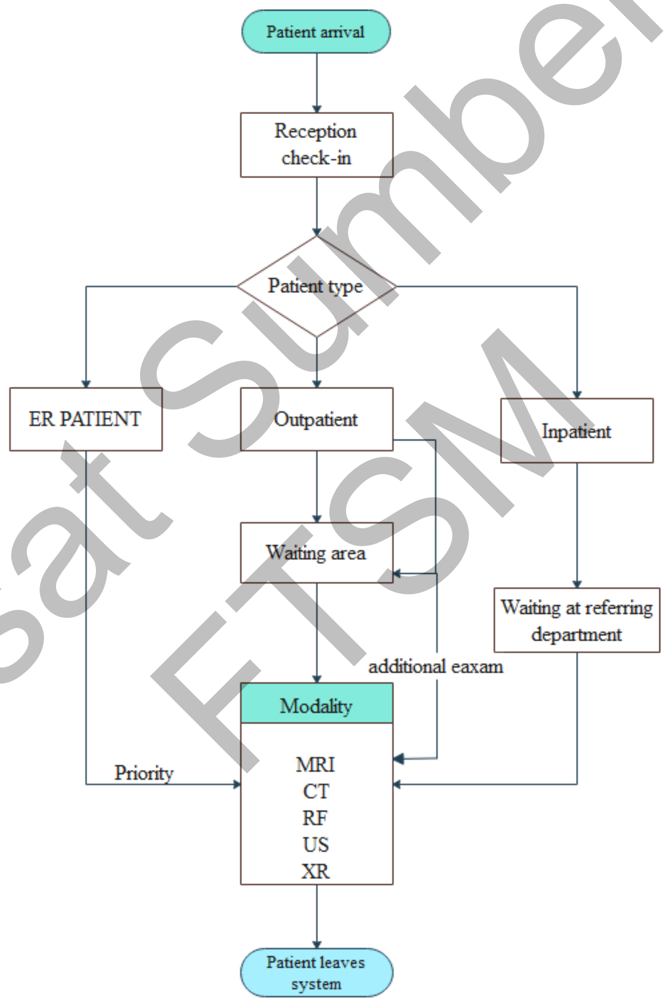


Figure 4.1- Patient Flow Diagram

The patient flow starts at the reception desk in the RD, where all arrival patients are supposed to check-in. The next step is waiting in the RD waiting area, where all arrival patients are waiting for the availability of their specialized radiology machine. The patients now go through with their procedures with a specific service time which was also discussed in 3.3.2. After completing their service(s), the patients then proceed to exit the system. Please refer to Figure 4.1, a diagram showing the RD's patient routing around. The reception check-in node input the patients' information and data into the system. The problem with the current state is that the system is not designed to record the data into the system with a specific rate to ensure that the change throughout the day is recorded. The current state does not mimic the facility's actual patient influx. This is a real challenge to the author on ensuring the model reflects the hospital's rush hours and accurately portrays patient waiting times and machine utilizations. Because of this problem, the data contain a lot of noise (i.e., error) and missing values. Therefore, the author has to collect data by observation. Based on the collected data, the following is the patients' arrival rate per hour is captured below in Figure 4.2.

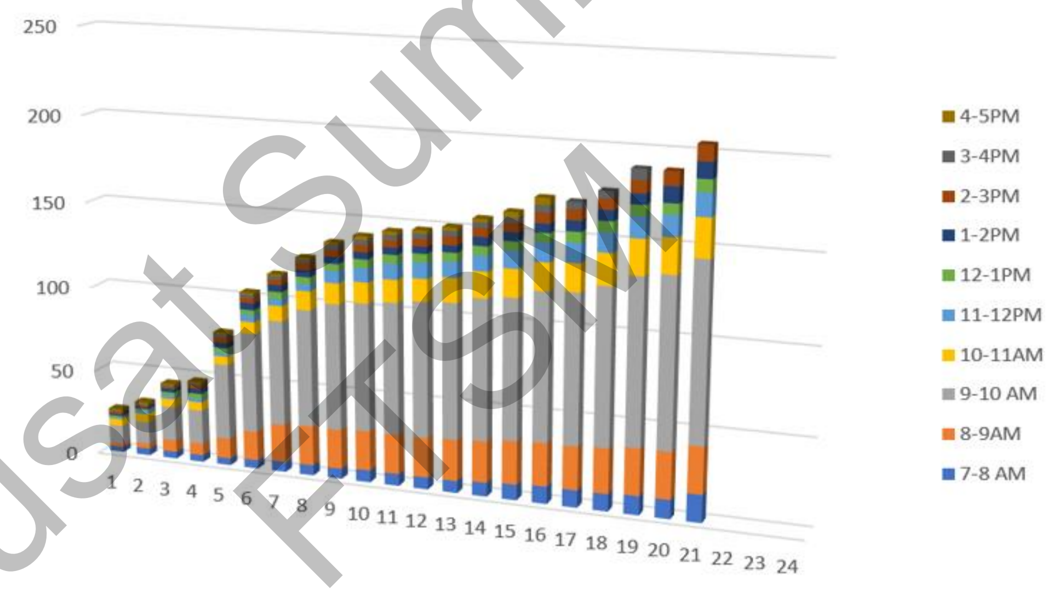


Figure 4.2– Patients' Arrival Rate per Hour Snapshot

After being injected into the system and completing the check-in processes, the patients proceed to the radiology desk where they wait for their procedures' availability, as shown in Figure 4.3. Figure 4.3 shows that the current queue discipline in the RD is multiple lines multiple servers.

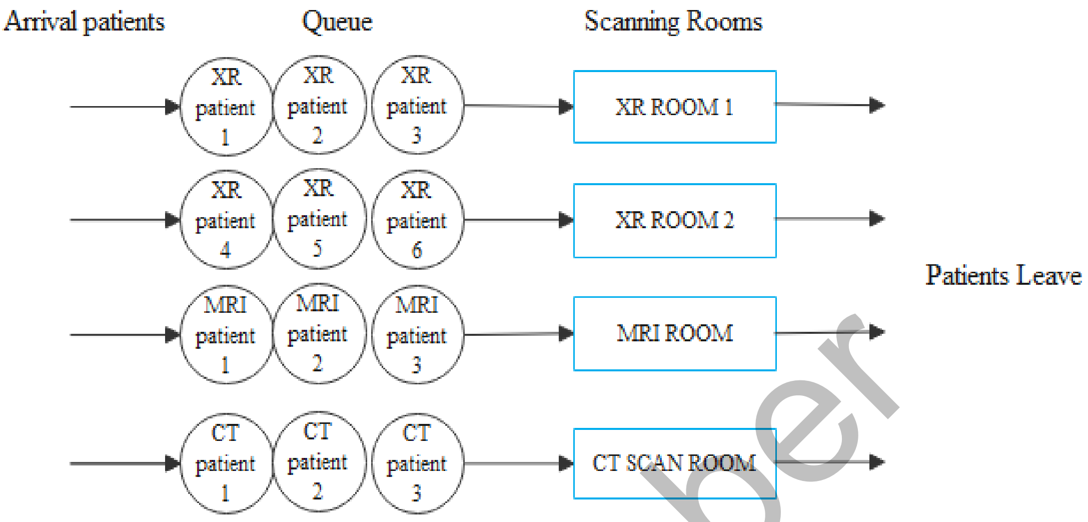


Figure 4.3 Multi-server, multiline single-phase types of queues in the RD

Queues or waiting lines are defined as lines of individuals or patients waiting for their turn to receive service from the technicians or service operator. Figure 4.3 shows that the current service system adopted by the RD, which is a multi-server, multiline single-phase type of queue. Multi-server systems have parallel service providers offering the same service, as shown in Figure 4.3, where there are two X-ray rooms. The characterized of the service system of the number of waiting lines and servers, the servers' arrangement, the patterns of arrival and service, and the priority rules of service. The service systems in the RD are:

i. Number of waiting lines: One channel (queue line) for each service (queue).

ii. Number of servers: The service for each room requires only a single activity. In the RD's single-phase system, the procedure/service is completed all at once.

iii. Arrangement of servers: Services require a single activity or a series of activities and are identified by the term phase. Refer to Figure 4.3. RD current state is in a single-phase system, the service is completed all at once. However, there are some cases that Dr requires more than one procedure, for example, a patient is ordered to have an X-ray and then a CT scan. If this case happens, for certain patients, it becomes multiple lines multiple phases.

iv. Arrival and service patterns: Patient's arrival based on our observation is similar to Poisson probability distribution, and service times can be described by an exponential distribution. Figure 4.4 shows the time between arrivals in the first time slot, where 0 means that there is no time between the arrival patient and the patient before him, and 2 means there is a gap of two minutes between the arrival patient and the patient before him.

v. Waiting line priority rules: A waiting line priority rule determines which customer is served next. The RD uses priority rule of "first-come, first-served". This priority rule selects patients based on who arrived first and therefore, has been waiting the longest in line.

Our observation findings are similar to Sharma (2013) statement that queue is formed when either the number of patients requiring service exceeds the number of supplies of service provider (RD facilities) or the technician/facilities do not perform efficiently well such that it takes more time than necessary to complete a procedure.

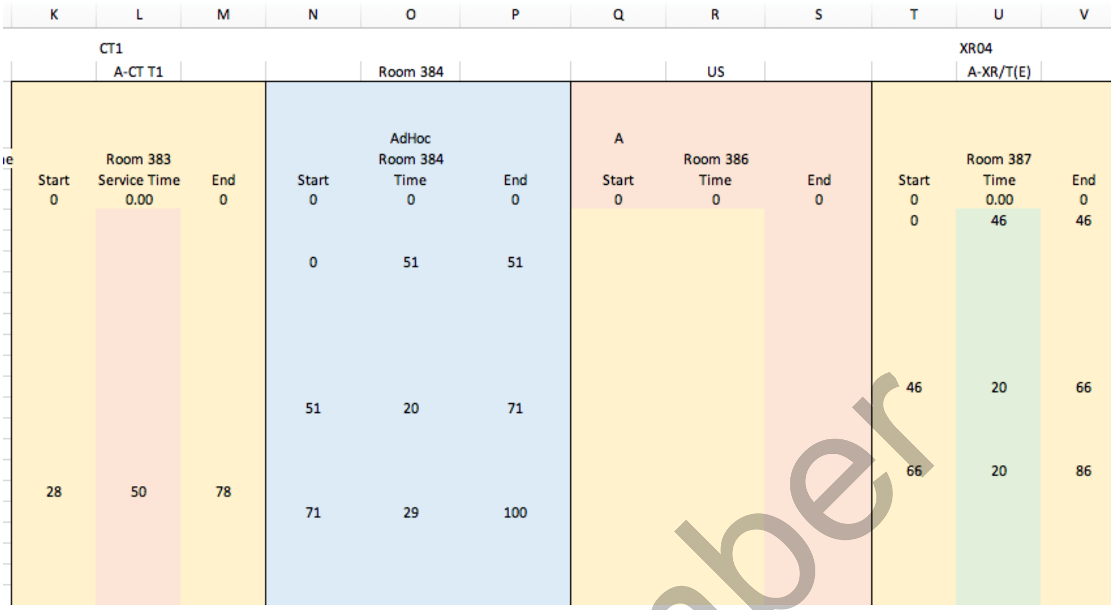
SIMULATION

Queuing at RD with Multiple Rooms

25 Patient Slot	Poisson Time btw Arrivals	ax Avg Wait TIme 101 patie Arrival Time
0	0	0
0	0	0
0	0	0
0	0	0
0	2	2
0	2	4
0	2	6
0	7	13
0	0	13

Figure 4.4: Microsoft Excel Process Properties

Figure 4.5 below highlights the multiple procedure paradigm incorporated in Microsoft Excel. This was thoroughly discussed in section 3.1.3, and below is a representation of that particular process flow using Microsoft Excel.



K	L	M	N	O	P	Q	R	S	T	U	V
CT1									XR04		
A-CT T1			Room 384			US			A-XR/T(E)		
				AdHoc		A					
Start	Room 383 Service Time	End	Start	Room 384 Time	End	Start	Room 386 Time	End	Start	Room 387 Time	End
0	0.00	0	0	0	0	0	0	0	0	0.00	0
									0	46	46
			0	51	51						
									46	20	66
			51	20	71						
									66	20	86
28	50	78									
			71	29	100						

Figure 4.5- Model Snapshot Multiple Procedures

After completing their required examinations, the patients then proceed to exit the system.

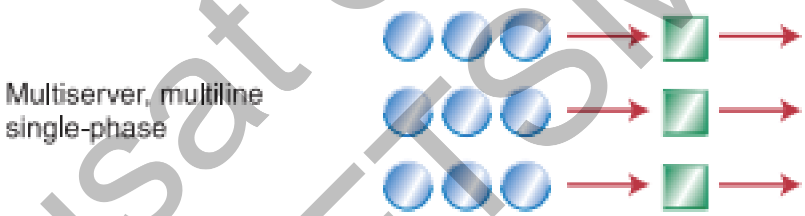


Figure 4.6. Multi-server, multiline single-phase exits

Now that the model is complete, we will be running it, discussing its results and outcomes to assess its performance and recommend fixes if the need arises. Details can be found in the next chapter.

4.2.4 Patient Arrival Time

The time between arrivals is the kick-starter of every model. In the existing system, the process starts when a patient comes to the hospital; in the model, however, the "Start" node 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, the below table (4.2) was populated. Similar arrival numbers were grouped under the same time epoch.

Table 4.2: Patient arrival time per hour

Time frame	Patient per hour	Mean
7-8 a	21	7.381
8-9AM	24	26.75
9-10 AM	24	70.875
10-11AM	24	13.7917
11-12PM	23	8.4783
12-1PM	24	4.875
1-2PM	22	4.8182
2-3PM	23	4.7391
3-4PM	19	2.6842
4-5PM	16	1.625

4.2.4.1 Patient type

There are different kinds of patients in the RD, and they can be divided based on characteristics such as the type of condition and the type of visit. Consequently, patients in the radiology department receive services depending on their properties; as mentioned, emergency patients are prioritized before the inpatients and outpatients based on their conditions. In addition, the outpatients may be prioritized over the inpatients; however, their services are also dependent on the type of visit. First-time patients may go through more procedures than the second and third.

The RD has Five central units: X-ray (XR), computed tomography (CT), ultrasound (US), Fluoroscopy (RF), and magnetic resonance imaging (MRI). In addition, the department provides radiological procedures to inpatients and outpatients on neonatal, pediatric, adolescent, adult, and geriatric patient age groups inpatient. Each patient type has a specific journey for using resources in the radiology department with different duration distribution. This journey is assigned to each patient in Microsoft Excel through the queuing module. In this module, the sequence of patient flow through the radiology department is defined, which is the ordered list of units that a patient must visit. In this study, patients are specified based on the patient arrival time, patient priority, the number of procedures to do.

4.2.5 Procedure service time

All radiology procedures were digitally imported from the RIS, cleaned, and processed using Microsoft Excel to find the below service time distributions. It is important to note that a triangular distribution of minimum 5, maximum 15, and most likely 10 minutes has been added to all service times as preparation time for the procedure. Figure 4.7 shows dataset snippet (in minutes) of MRI and Ultrasound.

MRI
range2 [1.333 - 4.083]
range3 [4.083 - 8.200]
range4 [8.200 - 14.800]
range1 [-∞ - 1.333]
range5 [14.800 - ∞]
Ultrasound
range2 [32.358 - 38.533]
range4 [43.283 - 56.842]
range5 [56.842 - ∞]
range1 [-∞ - 32.358]
range3 [38.533 - 43.283]

Figure 4.7-Dataset snippet

4.2.6 Travel Time and Waste-Time

The travel and waste time in the RD is the time that technicians take finding patients in the waiting area to take them to the examination room. After the first physician assessment, patients in the radiology department are expected to undergo an examination; however, the process is sometimes not directed since individuals are forced to wait in the waiting area until the technician calls them. Nevertheless, the preparation time is not accounted for when recording patient data in the database because the service time is recorded from the time a patient is tagged for examination to finishing it. According to the interview with the head of the radiology department, several reasons prolong the travel time as follows:

i. Waiting for patients who come back for multiple examinations
ii. Waiting for patients who need to be escorted by security
iii. Watching risk of violence (code white)
iv. Patients waiting to speak with a doctor
v. Patients who refuse to have a radiology examination
vi. Patients not ready at the time of the request
vii. Searching for a wheelchair
viii. Unable to find the nursing staff to help transfer a patient
ix. Cleaning that is necessary before and after isolated patients

In addition, besides the time spent on preparing a patient for an examination, technologists waste a considerable amount of time during their shifts. Time wastage during shifts stems from factors such as answering patients' questions and briefing colleagues about the day's procedures and answering their questions. Consequently, the travel time and waste time are sometimes hidden, but they should be accounted for in modeling. Noticeably the model by Delay block successfully integrated the hidden wasted time. In addition, some records sheets should be filled each day to list the reasons for delays in performing examinations and record the time wasted due to these reasons. The radiology department manager provided the sheet, and an approximation for the delay time in the emergency radiology unit was estimated accordingly. The Delay block allows the user to consider a constant or random distribution for the delay time during a process as it was done in this simulation modeling.

4.2.7 Service Stations

After assigning the type, sequence, and service time to all patients, the resources should be used. Different resources were modeled through the Station block. As discussed, there are five different resources in the radiology unit: XR, CT scan, MRI, RF, and the

US. Therefore, there are five stations plus one station for exiting the system. Technologists serve patients in each unit, and they were included in the simulation model as human resources. The resource(s) and the time an entity spends in a unit can be defined in the Process block.

4.3 THE OR QUEUE MODEL

This study proposes a mathematical model based on queueing theory concepts applied in optimization problems in healthcare. The mathematical model is designed to represent every process step that a patient goes through and the number of resources available. The model utilized in this study is developed as follows:

Index

j process step, j=1,2….., J where J is the total number of process steps

p patient type, p= 1,2….., P where P is the total number of patient types

Parameters:

S_j Service time for process j

μ_j Service rate of servers for process j

$$\mu_{j={}^{1}/_{S_j}}$$

$\lambda_{j,p}$ Patient arrival rate for process j

$\lambda_{j,p={}^{M_{j-1}}/_{S_{j-1}}}$ $\quad \forall j > 1, p \in p$

$\lambda_{1,p=1_p}$ $\quad \forall j = 1, p \in p$

I_p Initial arrival rate for patient p

$N_{j,min}$ Minimum number of resources at process step j

$N_{j,max}$ Minimum number of resources at process step j

Z_1 Objective function 1

Z_2 Objective function 2

$_{JW,p}$ Patient wait time of type p waiting for process j

$x_{j,p}$ Number of patients being served process j of type p

Objective Function

$Z_1 = Min \sum_j \sum_p w_{j,p}^{Wait}$ (4.31)

$Z_2 = Min \sum_j \sum_p c_{j\ *\ M_j}$ (4.3.2)

$Z_3 = Min\ w_{1\ Z_1} + w_{2\ Z_2}$ (4.3.3)

Subject to

Optimization Constraints

$N_{j,min} \leq M_j \leq N_{j,max}$
$\forall\ j \in J$ (3.4.4)

$C_j * M_j \leq B_j$
$\forall\ j \in J$ (3.4.5)

$w_1 + w_2 = 1$
$\forall\ j \in J$ (3.4.6)

$0 \leq w_1 \leq 1$
$\forall\ j \in J$ (3.4.7)
$0 \leq w_2 \leq 1$
$\forall\ j \in J$ (3.4.8)

Where

$$w_{j,p} = \sum_{k=1}^{j} w_{k,p} \qquad \forall\, j \in J, p \in p \;(4.3.9)$$

$$w_{j,p} = \frac{l_{j,p}}{\lambda_{j,p}} \qquad \forall\, j \in J, p \in p \;(4.3.10)$$

$$l_{j,p} = l_{j,p} - x_{j,p} \qquad \forall\, j = 1, p \in p \;(4.3.11)$$

$$l_{j,p} = l_{j,p} - x_{j,p-1,p} - X_{j,p} \qquad \forall\, j > 1, pp \in p \;(4.3.12)$$

$$x_{j,p} = \sum_{k=1}^{j} L_{k,p} \qquad \forall\, j, k \in J, p \in p \;(4.3.13)$$

$$L_{j,p} = \frac{}{(M_j - 1)!(M_j . \mu_j - \lambda_{j,p})^2}\, p_0 \qquad \forall\, j \in J, p \in p \;(4.3.14)$$

$$L_{j,p} = \frac{\lambda_{j,p*\mu_{j,p}\left(\frac{\lambda_{j,p}}{\mu_j}\right)^{m_j}}}{(M_j - 1)!(M_j . \mu_j - \lambda_{j,p})^2}\, p_0 + \frac{\lambda_{j,p}}{\mu_j} \qquad \forall\, j \in J, p \in p \;(4.3.15)$$

$$p_0 = \left(\left[\sum_{n=0}^{Mj} \frac{1}{n} \left(\frac{\lambda_{j,p}}{\mu_j}\right)^n \right] + \frac{1}{M_{j!}} \left(\frac{\lambda_{j,p}}{\mu_j}\right)^n \left(\frac{m_{j*}\,\mu_j}{m_{j*}\,\mu_j - \lambda_{j,p}} \right) \right)^{-1} \qquad \forall\, j \in J, p \in p \;(3.4.16)$$

Equation (4.3.1) is the objective function that minimizes the total waiting time for all patient types through the system at every stage. Equation (4.3.2) is the second objective function that minimizes the total cost of each resource per day in the system at every stage. Equation (4.3.3) is the third objective function that minimizes the weighted average of the first two objective functions. Equation (4.3.4) represents the control limits for the number of available resources. $N_{j,min}$ is the minimum number of resources allocated at process step j. $N_{j,max}$ is the maximum number of resources allocated at process step j. Equation (4.3.5) represents the constraint limiting the total cost under the daily budget. Equation (4.3.6) to Equation (4.3.8) defines the weights for objective function (4.3.3). Equation (4.3.9) calculates the (cumulative) total wait time for all patients for all process steps used in the objective function. Equation (4.3.10) shows the relationship between the queue length at each process step and the wait time. Equation

(4.3.11) to Equation (4.3.13) is used to calculate the number of patients in the queue at every step. Equation (4.3.14) to Equation (4.3.16) shows the relationship between the decision variable (number of resources) and the length of the queue. Finally, equation (4.3.14) to Equation (4.3.16) highlights the relation between the wait time and the number of resources.

4.4 THE PREDICTIVE MODEL FOR SERVICE TIME (S_J)

The main issue in developing a simulation model for the RD is the fact that the value of service time for process j (S_j) varies for each patient. This project is not the first Radiology Department that uses data mining and regression methods to define patient time in a system, and it is a data-driven study that uses accurate the RD data. Therefore, there is a need to develop a machine learning model to represent the relationship between S_j and patients' profiles. The fundamental question is, what is the best predictor to be used in predicting S_j?

In this phase, the prediction model was developed for the service time, exploited data mining and regression tools, and used RapidMiner software. The generic linear technique models the relationship between the explanatory variables, continuous or categorical, and the output.

4.5 SUMMARY

With increased patient waiting time in the healthcare system, developing a model that can enhance performance improvement is essential. However, it is essential to ensure that the model is similar to the existing system to ensure that the data collected is accurate enough for decision making. Noticeably, this can be successful by integrating the DES that can help identify problems in a system and predict future performance processes. The DES can enhance the development of an effective predictive model with the ability to collect efficient and accurate data necessary for decision-making.

CHAPTER V

EXPERIMENTAL RESULTS AND ANALYSIS

5.1 INTRODUCTION

The problem of patient wait times in hospitals has received adequate attention in recent years based on its effects on the provision of quality care. One of the factors that accompany long waiting times in hospitals is that some patients go home without the first consultation with the doctors increasing the risk for adverse effects (Bentayeb et al., 2018). However, service time prediction through the simulation of queuing analysis has proven to be effective in determining possible interventions for reducing patient waiting times.

This chapter will outline all the experimental design and analytical results to the methodologies extensively discussed in Chapter 3 to develop an effective patients' waiting time reduction tool. The data collected, utilized, and analyzed for this study was from RIS and observations conducted at the RD at the hospital, Saudi Arabia. Noticeably, this study's primary key performance indicators (KPI) are patients waiting time and staff's idle time and overtime. This KPI is determined during the discussion with the head of the department. This study explored the impact on patient wait times and technician idle time when using a data mining technique to predict the service time. The simulation technique is used to study the impact of assigning a type of patients to a fast track or separate unit for low-acuity patients in the RD using an operational research queue-based Monte Carlo simulation in a spreadsheet-based decision support tool.

5.2. RESULTS OF TIME STUDY DATA ANALYSIS

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.

5.2.1 RD Historical Data Summary for May 2021

The RD is a complex department based on the sense that it provides a wide range of diagnostic imaging services, and it operates on paperless and filmless concepts. The primary services provided in the department include CT scanning, MRI scanning, Ultrasound, Fluoroscopy, and X-Ray. Consequently, it was vital to use a system that could enable the evaluation of these concepts and the management of the department's complex processes; RIS and Picture Archiving and Communication System (PACS) were employed.

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 5.1 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 5.2 summarizes the incoming patient population for services in May 2021 at the RD.

Table 5.1: average served patients

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

Table 5.2: Incoming Patient Population in May 2021

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

On the other hand, it was essential to record all the explanatory facets; table 5.3 presents patients' characteristics in terms of their gender, while Figure 5.1 and Table 5.4 present the exogenous factors such as the type of procedures within the study period (May 2021). According to table 5.3, the number of male patients in the department during the time of the study was significantly higher than that of female patients. The percentage of male patients was 62.2%, while that of the females was 37.3%. At the same time, the results of exogenous factors proved that X-ray procedures are most demanded in the department, followed by CT and ultrasound. MRI, MRCP, Enema Trisapeutic water-soluble, Urethrocytogram, MRCP W/C, MR Venography Cerebral Veins, and Cystogram are the least demanded. From the study, the number of patients demanding X-RAY in the department was 2137, which is approximately 74.48% of all the patients in the department, while Urethrocytogram, MRCP W/C, MR Venography Cerebral Veins, and Cystogram had one patient each accounting for approximately 0.01% of all the patients in the department.

Table 5.3: Number of Patients by Gender

	Number of Patients	Fractions
MALE	1799	62.7%
FEMALE	1069	37.3%

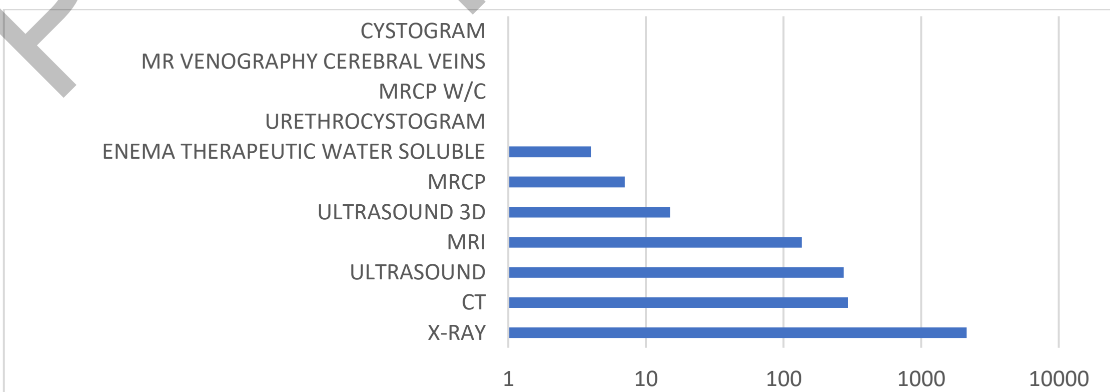


Figure 5.1: Type of Procedure Performed in May 2021

Table 5.4: Type of Procedures Performed in May 2021

TYPE OF PROCEDURE	# PATIENTS
X-RAY	2137
CT	293
ULTRASOUND	273
MRI	136
ULTRASOUND 3D	15
MRCP	7
ENEMA TRISAPEUTIC WATER SOLUBLE	4
URETHROCYSTOGRAM	1
MRCP W/C	1
MR VENOGRAPHY CEREBRAL VEINS	1
CYSTOGRAM	1

In addition, the evidence extricated further establishes the mean delayed or early arrival times of patients. At the RD conveniences, there are far-reaching delays in patient appearance times on account of restraints and inclinations of the individuals. However, impediments in patient arrivals concerning the due appointment time conceive bottlenecks and increases wait times for patients. Table 5.5 shows the average time a patient appears early or late for the appointment. The evidence shows a significant balance between the ordinary times a patient reports early or late for the appointment. The model, therefore, assumes that some patients are not on time in the time of conspiring the simulation model leading to an increment of waiting times.

Table 5.5: Mean Late/Early Patient Arrivals in Minutes

	Late Arrivals	Early Arrivals
Average	81.20	51.85
Std. Dev	80.57	43.66
Min	6.02	4.42
Max	435.08	133.1

The extracted RIS system data was used to evaluate the patient arrival rate per hour during the operational hours for services. 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 their operation at 8 AM, with 60% of the patients arriving in the first two hours. Similarly, Figure 5.2 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 arrived 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 longer because patients did not adhere to the appointment time assigned to them. In addition, the hospital allows patients to be registered even if they come too early than the allocated slots.

Table 5.6: Patient Arrival Time Pattern

From	To	Freq	Cumulative
7:00	8:00	3	2.941176
8:00	9:00	33	35.29412
9:00	10:00	26	60.78431
10:00	11:00	13	73.52941
11:00	12:00	10	83.33333
12:00	13:00	4	87.2549
13:00	14:00	5	92.15686
14:00	15:00	7	99.01961
15:00	16:00	1	100

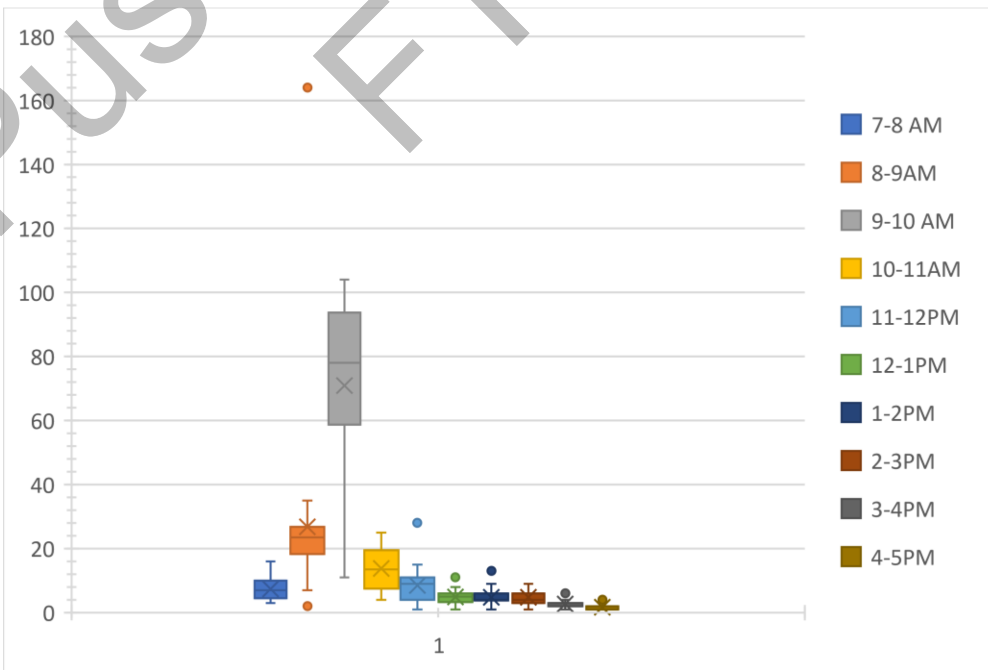


Figure 5.2: Boxplot Patients Arrival per Hour

Table 5.7: Patients Arrival per Hour for May 2021

	N	Min	Q_1	Median	Q_3	Max	Mean	Std Dev
7-8 AM	21	3	5	7	10	16	7.381	3.1698
8-9AM	24	2	20.75	23.5	26.25	164	26.75	30.4277
9-10 AM	24	11	60.25	78	91.25	104	70.875	29.2237
10-11AM	24	4	8.5	13.5	18.5	25	13.7917	6.6003
11-12PM	23	1	4	9	11	28	8.4783	5.9457
12-1PM	24	1	3.75	5	6	11	4.875	2.2129
1-2PM	22	1	4	4	5.75	13	4.8182	2.7192
2-3PM	23	1	3	4	6	9	4.7391	2.4903
3-4PM	19	1	2	3	3	6	2.6842	1.2933
4-5PM	16	1	1	1	2	4	1.625	0.8851

5.2.2 Type of Procedures

The time study observations of 102 patient appointments in 5 days (4th to 8th of May 2021) were recorded and observed. The data collected was filtered and analyzed to evaluate the estimated patient arrival rate and patients' type of 52 procedures and two types of patients: out-patient and in-patients. Figure 5.3: shows the number of patients and procedures per day that were observed, and Table 5.8 shows the average patient arrival rates per hour on a given day. X-Ray is the most requested procedure, between 68% and 81% of the requested procedures in a day.

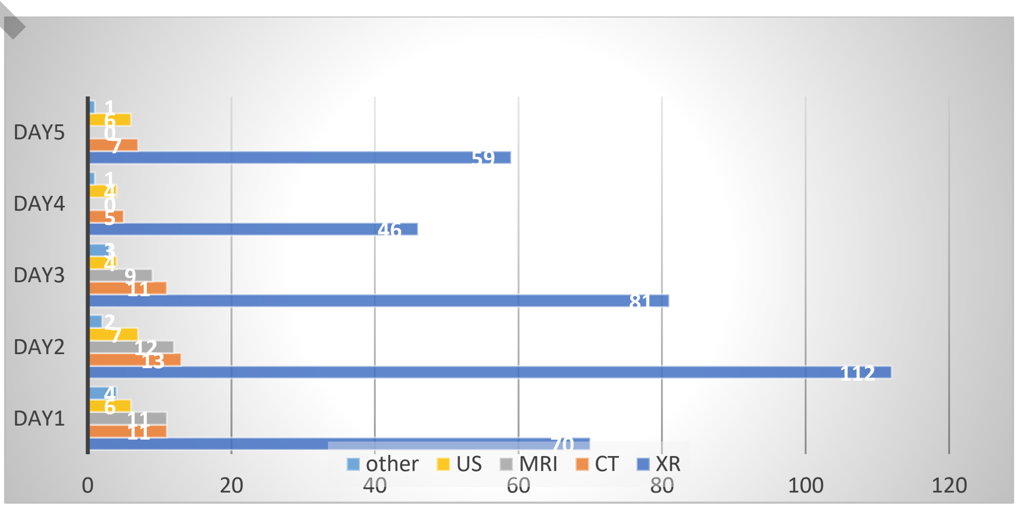


Figure 5.3: Observed Patients of Procedures

Table 5.8: the average patient arrival rates per hour

	Min	Max	Average arrivals
7-8 AM	3	16	9.5
8-9AM	2	164	83
9-10 AM	11	104	57.5
10-11AM	4	25	14.5
11-12PM	1	28	14.5
12-1PM	1	11	6
1-2PM	1	13	7
2-3PM	1	9	5
3-4PM	1	6	3.5
4-5PM	1	4	2.5

5.2.3 Service Time, Idle Time, and Overtime Study Observations

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 5.4 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.

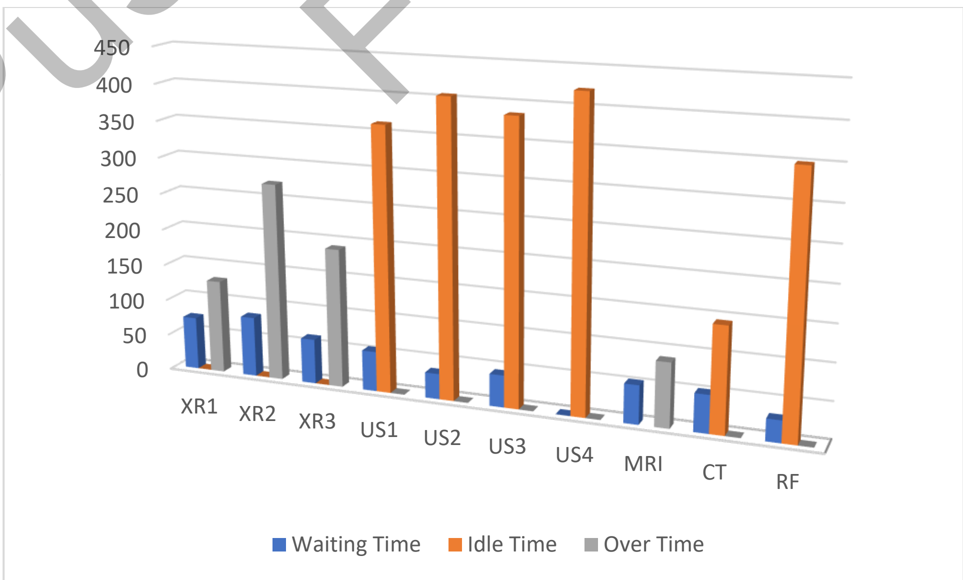


Figure 5.4: Current average waiting time, idle time, and overtime for all rooms

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.

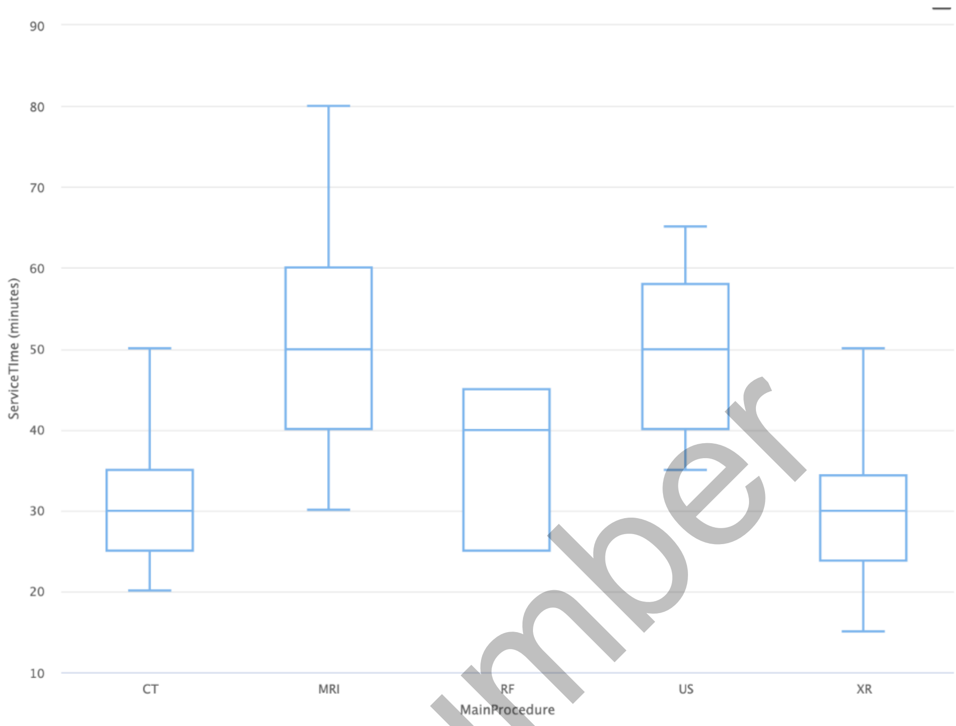


Figure 5.5: Box Plots for Process Time.

5.3 RESULTS FOR SIMULATION MODEL

Microsoft Excel is used in developing the simulation model. Consequently, the model is designed to simulate the scanning process as expressed in Chapters 1 and 3, representing the RD accompanying ten rooms: this section details current state analysis and optimization. Section 5.4 will confer the second simulation model to evaluate the future condition if the service is augmented to extra rooms accompanying increased resources.

5.3.1 Input Parameters: Current State

The simulation was designed with the following input parameters.

1. Scheduled patient arrivals translated into arrival rates per hour as described in Section 5.2.1.
2. Resource allocation and availability as discussed in Section 5.2.3.
3. The processing time (service time) for each resource at every process station is defined by the distributions in Section 5.2.3 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. Sections 5.2.2 and 5.2.3 show the patient's route corresponding to the patient type.
5. The simulation model's output is the Average Wait Time (AWT) and Average Idle Time (IWT) for staff.

5.3.2 Output Analysis: Current State

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, as delineated in Chapter 3. Table 5.9 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 5.9.

Table 5.9: Comparison between observed waiting time and simulation waiting time

	Observed Average Waiting Time (mins)	Mean Simulation Average Waiting Times(mins)
XR1	72.78	68.45
XR2	82.79	80.32
XR3	61.82	60.05
US1	55	57
US2	35	36
US3	44	42
US4	0	0
MRI	53.04	47.19
CT	51.63	65.42
RF	30	29

During the observation, the following rooms were found to be underused. However, the problem was not serious, as mentioned in Section 5.2.3:

a. US1
b. US2
c. US3
d. US4
e. RF

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

a. XR1
b. XR2
c. XR3
d. MRI
e. CT.

5.3.3 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

Table 5.10: Comparison between the observed data and simulation data

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

5.4 SENSITIVITY ANALYSIS

For every simulation study, sensitivity evaluation is a substantial facet to test the gravity of each decision variable on the model. Sensitivity analysis serves as an authentication of the simulation model since variation in the decision variables should produce a sensible gain result. The effects and interplays of the decision variables are further noticed through the analysis. Noticeably, to analyze the main effects and interplays for the outcome variables, the study uses the results produced by the developed Spreadsheet Based DSS by means of a synopsis and observes the change in average wait time for patients' processes. The main effects and synergy plot is delineated in the following figures.

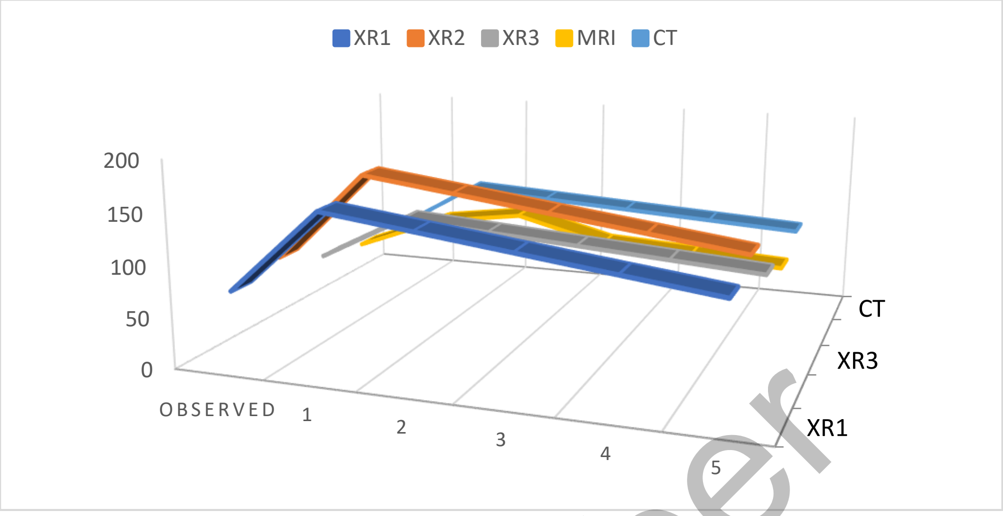


Figure 5.6: Main effect plots when arrival times intervals are changed between 1-5 minute

The main effects plot is used to observe the change and effects of changing the service time on mean wait time for patients at corresponding rooms. In Figure 5.6, the main effects plot shows the changing arrival times intervals between 1-5 minutes. Figure 5.7 shows a significant improvement in wait time when the minimum service time (minimum value found in the collected data) is used or when the service time is decremented. The figure also shows that due to the increase in the number of service times (maximum value found in the collected data), the wait time for the patients will increase.

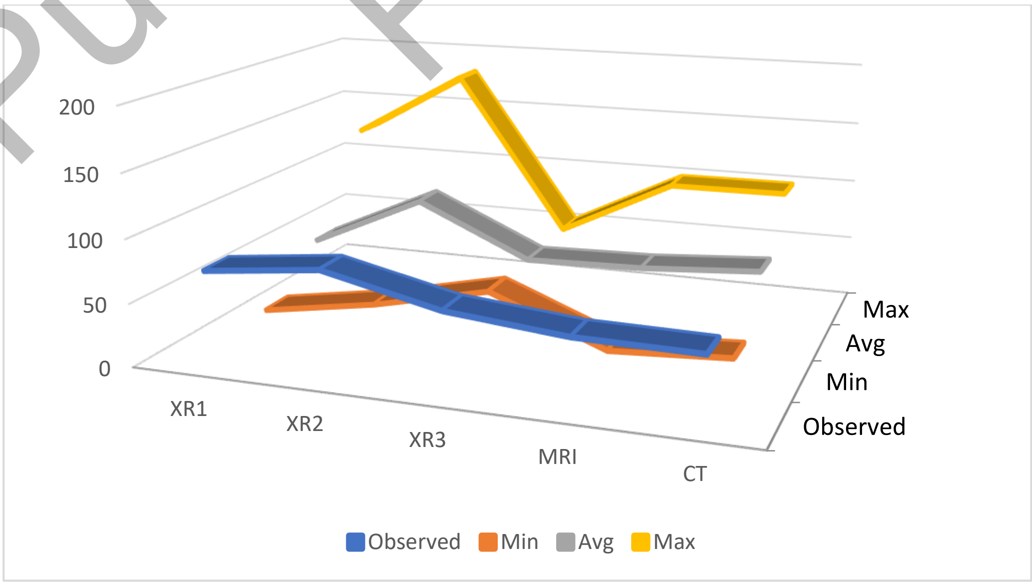


Figure 5.7: Main effect plots when service time values are fixed to the minimum, maximum and average service times

Figure 5.7 considerably shows the increase in the waiting time regarding the change in service time. It shows that the service time should diversify from one patient to another. It further illustrates that if the working time of the RD is fixed into a certain period, such as 30 minutes per slot, it does not guarantee that the waiting period is going to be upgraded because of the disposition of extreme inconsistency in the service time on account of the ramifications of procedures or the difficulties that patients experience when moving from one place to the other. Hypothetically, the decision variables like the number of rooms and staff contribute considerably to reducing the wait time. Similar to services, the increase in the number of rooms or technicians may cause a decrease in wait time for the procedure. However, the wait time will be nearly relative or even more significant if the systems sequence management is not revised. Thus, it is critical for this study to suggest a procedure that efficiently forecasts service time. The front office can use the predicting model to designate patients in accordance with their envisioned service time.

5.5 FUTURE STATE SIMULATION MODEL

This section discusses the analysis and results of the simulation model designed to evaluate the future state of the RD queue systems when the queue system is changed to single line multiple servers' discipline to reduce the waiting time. Furthermore, the input parameter of service time is replaced by a predictive model.

5.5.1 A Queue Model Using Single Line Multiple Server

Table 5.11 compares the current queue management system and the proposed single-line multiple server systems. As evident in the table, implementing the single proposed line multiple server systems has varying effects on different rooms in the RD. XR1, XR2, and CT are affected positively by the system based on the sense that the waiting time is reduced. However, the system is ineffective in other rooms, such as the MRI, since it leads to a sudden increase in the waiting times. In addition, the table indicates that there is a positive relationship between implementing the system and the reduction of overtime. The proposed system illustrates an improvement in overtime, where the average overtime and total overtime decreased by 65.52%. These results indicate that the introduction of waiting time reduction tools should be based on a consideration of other factors such as a patient's condition. In as much as the implementation of new systems is aimed at increasing the quality of services provided and solving problems experienced on care providence, sometimes the systems may not be effective, especially when key factors such as patient's health conditions are overlooked during the development process.

Table 5.11: Comparison between Current Queue System and Proposed Single Line Multiple Server System

	Observed Waiting Time	Simulation Waiting Time	Observed Overtime	Simulation Overtime
XR1	72.78	64.3526956	129	35.62
XR2	82.79	74.6001972	272	0
XR3	61.82	99.0653934	191	2.59
US1	55	64.3526956	0	0
US2	35	74.6001972	0	0
US3	44	99.0653934	0	0
US4	0	25	0	0
MRI	53.04	302.66004	88	196.25
CT	51.63	25.85	0	0
RF	30	159.589411	0	0
Average	48.606	98.9136024	68	23.446
Total	486.06	989.136024	680	234.46

5.5.2 A New Appointment by Slot Policy

Table 5.12 shows the connection between the waiting time and overtime before and after the implementation of the simulation model in the various Radiology department rooms. Evidently, there is a conclusive relationship between the application of the simulation model and a decrease in the patient waiting time and overtime in the XR1, XR2, and XR3. The simulation waiting time and overtime are decreased considerably in the rooms before and after the application of the new slot time policy. These results substantiate that the inauguration of new queuing management strategies in the healthcare plan can lead to a decline of patient waiting times and overtime even without an increase in resources. However, the installation of the new slot time policy is detrimental for the MRI, US2, US3, and the simulation overtime for the CT room. The introduction of new service schedules in the healthcare system should vary based on the sense that sometimes the waiting times are contingent upon an individual's condition. In most cases, patients with severe injuries are more exposed to the risk of suffering from heightened waiting times because they need more attention and also the fact that they face extreme troubles when moving from one place to the different. For that, the MRI department's simulation waiting time and overtime dramatically increased before and after the request of the new slot time policy.

Table 5.12: Appointment by Slot time Policy

			Without The Slot Time		With New Slot Time Policy	
	Observed Waiting Time	Observed Overtime	Simulation Waiting Time	Simulation Overtime	Simulation Waiting time	Simulation Overtime
XR1	72.78	129	64.35	35.62	65.59	178.35
XR2	82.79	272	74.6	0	47.06	117.15
XR3	61.82	191	99.07	2.59	77.93	147.95
US1	55	0	64.35	0	0	0
US2	35	0	74.6	0	0	0
US3	44	0	99.06	0	0	0
US4	0	0	25	0	0	0
MRI	53.04	88	302.66	196.25	63.78	115.29
CT	51.63	0	25.85	0	14.66	139.1
RF	30	0	159.59	0	0	46.09
Average	48.606	68	98.91	23.446	26.902	74.393
Total	486.06	680	989.14	234.46	269.02	743.93

5.5.3 Service Time Predictive Model

This project found that the Support vector machine (SVM) is the best-supervised learning method for regression; compared to other algorithms, the SVM has the lowest relative error rate, as shown in Figure 5.8. Thus, SVM is used in this project to predict service time with a well-fitted regression model. Specifically, SVMs types used in RapidMiner have based on Java implementation of the SVM. There are uses for this learning machine method, where can use it in regression and classification, also it provides a fast algorithm. According to McGregor (2020), the linear SVM algorithm is better than some other algorithms, such as k-nearest neighbors, because the linear SVM algorithm chooses the best line in order to classify the data points. It selects the line that divides the data and is as far from the nearest data points as feasible. It is worth noting that 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 vector orthogonal 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, the kernel model consists of seven attributes which are: 1) Nationality; 2) MainProcedure; 3) Patient_Type; 4) Gender; 5) Procedure_Name, 6) Type, and 7) Age. Each of these attributes is represented by the 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

Figure 5.8 Algorithms comparison

In addition, in this project Weight by Correlation (WBC) operator was used. WBC calculates the attributes' relevance by computing the correlation value for each attribute in the data set. This weighting scheme is based upon correlation, and As attribute weight, it returns the absolute or squared value of correlation. The greater the weight of an attribute, the more important it is thought to be. Figure 5.9 below shows that the main procedure attribute has the highest weight at 0.647. A correlation is a number ranging from -1 to +1 that indicates the degree of association between two attributes. (e.g., gender and service time). A positive correlation value indicates a favorable link.

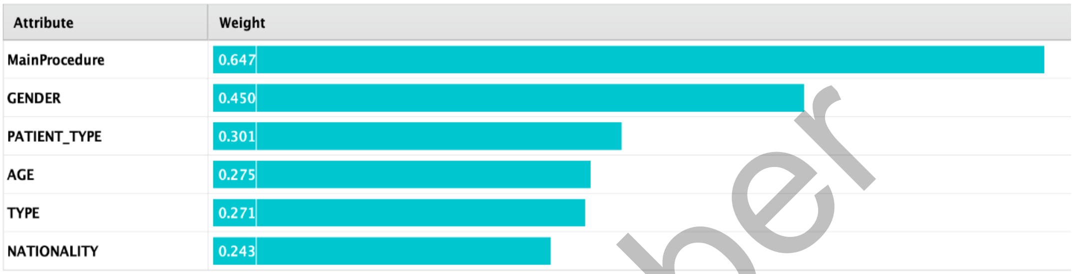


Figure 5.9 Weights by Correlation

Figure 5.10 below shows that Procedure-name has the highest weights that support the prediction of services time. In contrast, patient_type has the least value of weight in predicting a patient's service type.

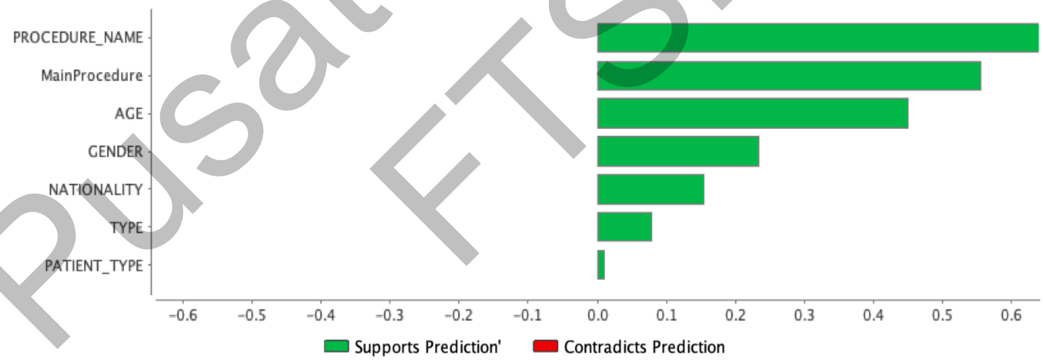


Figure 5.10 Weights by Correlation

The following Figure 5.11 shows a matrix of correlation (value between -1 and +1) that estimates the degree of relationship between two attributes (call them X and Y). A positive value for the correlation indicates a positive association. A negative value for the correlation indicates a negative or inverse connection. This matrix was produced by RapidMiner using the Weight by Correlation operator, where it calculates the weight of attributes with relation to the label attribute by using correlation. The greater the weight of an attribute, the more important it is thought to be. Figure 5.11 below clearly shows that Main Procedure has the highest correlation with the Service Time.

Attributes	AGE	GENDE...	MainPr...	MainPr...	MainPr...	MainPr...	NATIO...	NATIO...	NATIO...	NATIO...	NATIONALITY...	NATIONA...	PATIENT_...	ServiceTIme (min
AGE	1	-0.090	0.042	0.271	-0.038	-0.190	0.057	-0.094	-0.091	0.002	0.011	0.093	0.132	0.275
GENDER = Male	-0.090	1	0.086	-0.261	-0.080	0.166	0.130	0.064	-0.141	0.161	-0.219	0.054	0.251	-0.450
MainProcedure = CT	0.042	0.086	1	-0.121	-0.094	-0.514	-0.070	-0.035	-0.190	0.585	-0.049	-0.044	0.118	-0.076
MainProcedure = MRI	0.271	-0.261	-0.121	1	-0.094	-0.514	0.093	-0.035	-0.124	-0.087	0.179	0.031	-0.403	0.519
MainProcedure = US	-0.038	-0.080	-0.094	-0.094	1	-0.401	-0.055	-0.027	0.049	-0.068	-0.038	0.032	-0.124	0.360
MainProcedure = XR	-0.190	0.166	-0.514	-0.514	-0.401	1	0.028	0.067	0.222	-0.280	-0.057	-0.073	0.272	-0.510
NATIONALITY = BENGALI	0.057	0.130	-0.070	0.093	-0.055	0.028	1	-0.020	-0.262	-0.051	-0.029	-0.112	0.112	-0.033
NATIONALITY = KUWAITI	-0.094	0.064	-0.035	-0.035	-0.027	0.067	-0.020	1	-0.129	-0.025	-0.014	-0.055	0.055	-0.147
NATIONALITY = SAUDI	-0.091	-0.141	-0.190	-0.124	0.049	0.222	-0.262	-0.129	1	-0.324	-0.184	-0.720	-0.141	0.039
NATIONALITY = SUDANESE	0.002	0.161	0.585	-0.087	-0.068	-0.280	-0.051	-0.025	-0.324	1	-0.035	-0.139	0.139	-0.154
NATIONALITY = UGANDAN	0.011	-0.219	-0.049	0.179	-0.038	-0.057	-0.029	-0.014	-0.184	-0.035	1	-0.078	-0.088	0.221
NATIONALITY = YEMENI ...	0.093	0.054	-0.044	0.031	0.032	-0.073	-0.112	-0.055	-0.720	-0.139	-0.078	1	0.090	0.023
PATIENT_TYPE = IP	0.132	0.251	0.118	-0.403	-0.124	0.272	0.112	0.055	-0.141	0.139	-0.088	0.090	1	-0.301
ServiceTIme (minutes)	0.275	-0.450	-0.076	0.519	0.360	-0.510	-0.033	-0.147	0.039	-0.154	0.221	0.023	-0.301	1
TYPE = urgent	0.214	0.146	0.169	-0.279	-0.082	0.150	0.172	0.085	-0.042	0.213	-0.166	-0.088	0.650	-0.271

Figure 5.11 The Matrix of correlation

Support Vector Machine

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 5.12 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.

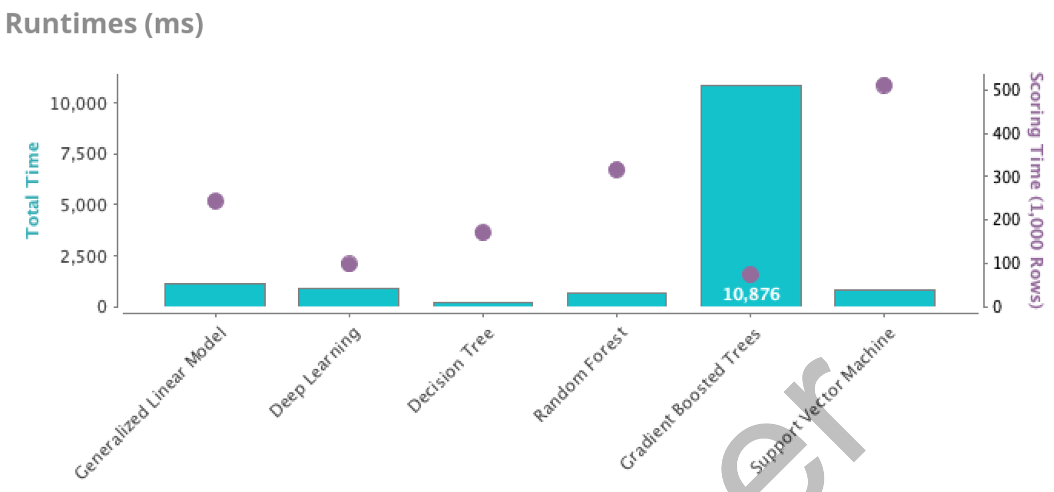


Figure 5.12 Runtimes

The Relative Error is shown in Figure 5.13, where the SVM and FR algorithms had superior relative error rates 15%, while GLM and GBT were performed the worst on this measure with 19% and 21%, respectively.

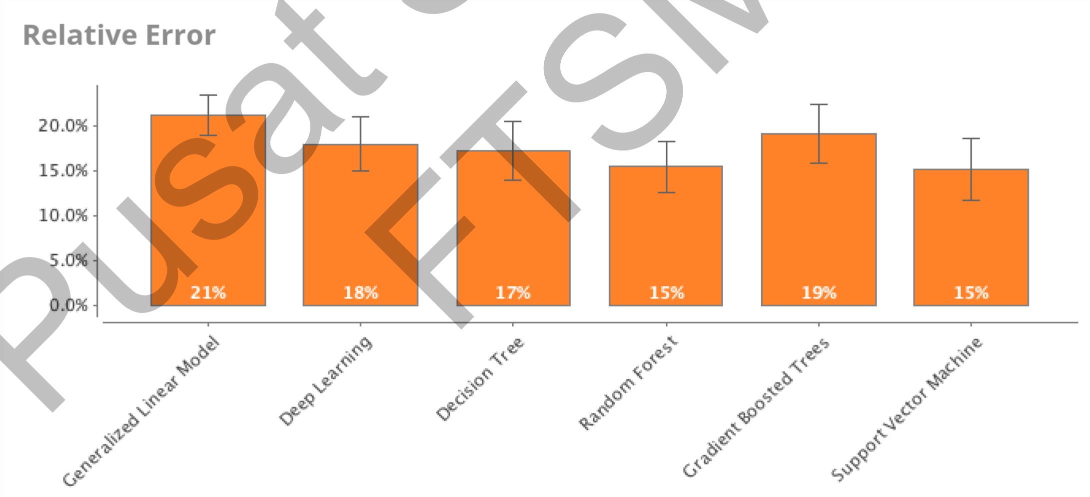


Figure 5.13 Relative Error

The following figures 5.14, 5.15, 5.16, and 5.17 are graphs that describe the used variables and attributes in this project.

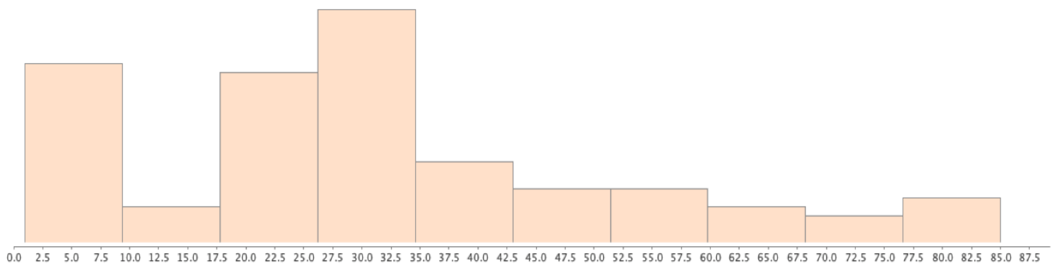


Figure 5. 14 Age

Minimum	1
Maximum	85
Average	31.843
Standard Deviation	21.206

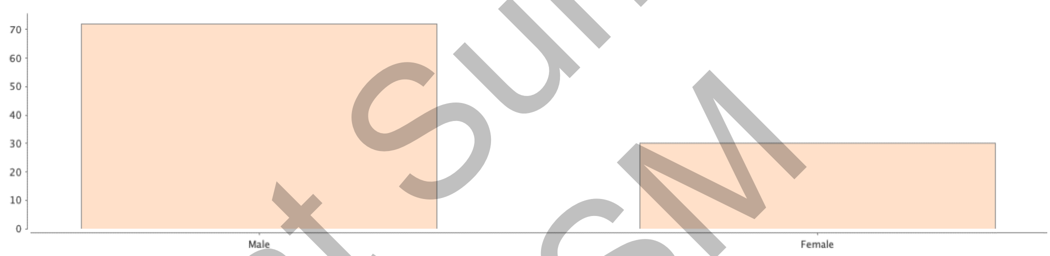


Figure 5. 15 Gender

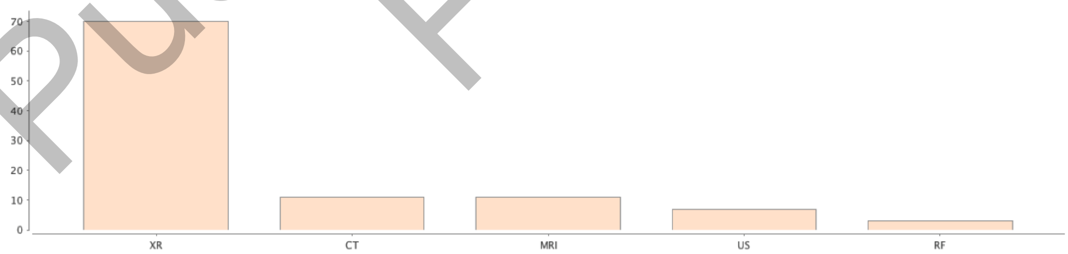


Figure 5.16 Main procedure

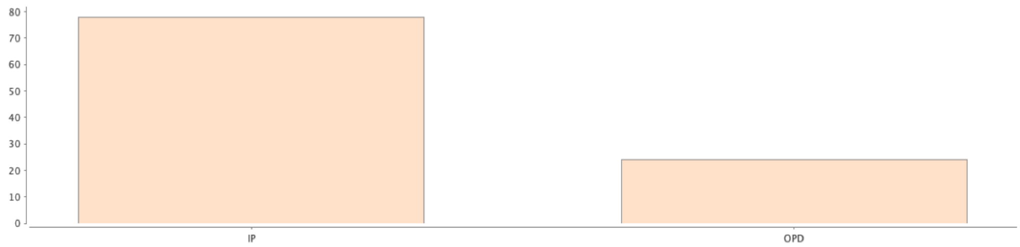


Figure 5. 17 Type of patients

a. Using the SVM Model to Separate Complex Cases from Normal Cases

Table 5.13 shows the outcome of using the SVM model to predict the service time of patients. The SVM model's main objective is to separate complex cases that require X-Ray services from the patients who require standard services (i.e., patients with typical cases). In this experiment, Room XR3 is assigned to handle complex cases.

The experiment results using the developed simulation show that the average waiting time for Simulation 3 has decreased from 74.39 to 40.44 minutes. However, the total overtime has increased from 743.93 minutes to 820.15.

Table 5.13: Comparison of results using the SVM model to predict service time

	Current state		Without The Slot Time		With New Slot Time Policy	Using SVM Model to Predict Service Time and separate complex cases into XR3	
	Observed		Simulation 1		Simulation 2	Simulation 3	
	Waiting Time	Overtime	Overtime	Waiting Time	Overtime	Waiting Time	Overtime
XR1	72.78	129	35.62	65.59	178.35	130.52	299.89
XR2	82.79	272	0	47.06	117.15	95.21	218.24
XR3	61.82	191	2.59	77.93	147.95	12.43	125.41
US1	55	0	0	0	0	0	0
US2	35	0	0	0	0	0	0
US3	44	0	0	0	0	0	0
US4	0	0	0	0	0	0	0
MRI	53.04	88	196.25	63.78	115.29	119.72	159.23
CT	51.63	0	0	14.66	139.1	42.77	17.38
RF	30	0	0	0	46.09	3.83	0
Average	48.606	68	23.446	26.902	74.393	40.448	82.015
Total	486.06	680	234.46	269.02	743.93	404.48	820.15

b. Using the SVM Model and Additional Resources

Table 5.14 shows the result of using the SVM model in order to predict patients' service time. The SVM model's primary purpose is to add an additional resource (new XR4) for complex cases.

The experiment outcome of using the developed simulation illustrates that the average waiting time dropped from 48.06 minutes to 16.13 minutes. In addition, the total overtime was reduced from 680 minutes to 663.99 minutes.

Table 5.14: Comparison of results using the SVM model to predict service time

	Group 1		Group 2		Group 3	
	Current State (Observed)	Current State (Observed)	Simulation Using SVM Model with Dedicated Room for Complex Cases		Simulation Using SVM Model with New XR Room for Complex Cases	
	Waiting Time	Overtime	Waiting Time	Overtime	Waiting Time	Overtime
XR1	72.78	129	130.52	299.89	16.09	168.77
XR2	82.79	272	95.21	218.24	17.93	138.95
XR3	61.82	191	12.43	125.41	46.74	11.12
New XR4					21.95	167.78
US1	55	0	0	0	0	0
US2	35	0	0	0	0	0
US3	44	0	0	0	0	0
US4	0	0	0	0	0	0
MRI	53.04	88	119.72	159.23	28.22	159.99
CT	51.63	0	42.77	17.38	42.77	17.38
RF	30	0	3.83	0	3.83	0
Average	48.606	68	40.448	82.015	16.13909	60.36273
Total	486.06	680	404.48	820.15	177.53	663.99

A paired t-test is performed to statistically justify that the results of employing the projected resolution (that is, SVM model and new resource) are considerably dissimilar. Noticeably, the t-test results reinforce that the p-value is inferior to the implication level of 0.05, justifying that the recommended solution is conclusive. Noticeably, a paired t-test is commonly used to equate the resources of two samples when all the facets in the individual sample perform in the added sample. Consequently, the following is the output of the paired t-test in this study. It shows that the p-value for equating the observed phenomenon evidence and the projected resolution is 0.0047; hence statistically justifying the results are considered peculiar and not equal. The study accordingly substantiates the projected solution using the SVM model, and additional resource allocation (that is, individual room for X-Ray procedures) has the slightest average patient wait period. P-value and statistical significance:

The two-tailed P value equals 0.0047
By conventional criteria, this difference is considered to be very statistically significant.

Confidence interval:
The mean of Observed minus SVM + NewResource equals 29.2360
95% confidence interval of this difference: From 11.4730 to 46.9990

Intermediate values used in calculations:
t = 3.7233
df = 9
Standard error of difference = 7.852

Group	Observed	SVM+NewResource
Mean	46.6060	17.3700
SD	23.3883	17.8116
SEM	7.3960	5.6325
N	10	10

5.6 SUMMARY

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.

CHAPTER VI

CONCLUSIONS AND FUTURE WORK

6.1 INTRODUCTION

This section introduces the conclusion of this work done. The organization of this chapter is as follows; Section 6.2 represents the project summary and section 6.3 describes project achievement and completion. While section 6.4 describes the project contribution. The limitations of this study are presented in section 6.5. Finally, some possible future research directions are presented in section 6.6.

6.2 RESEARCH WORK SUMMARY

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.

6.3 PROJECT ACHIEVEMENT AND COMPLETION

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 questions and reported in Chapters 4 and 5.

I. How to model the current queuing situation in the RD? The question is answered by the research methodology which is reported in Chapter 3.

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 which has been discussed in Chapter 5. 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. Please refer to Chapter 5.

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.

6.4 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.

6.5 LIMITATION OF THE SYUDY

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.

6.6 FUTURE WORK

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

REFRENCE

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.

Abo-Hamad, W., & Arisha, A. (2013). Simulation-based framework to improve patient experience in an emergency department. *European Journal of Operational Research*, 224(1), 154-166.

Adesina, O. S. (2018). Modelling Queuing System With Inverse Gamma Distribution: A Spreadsheet Simulation Approach

Aeenparast, A., Maftoon, F., Farzadi, F., & Yahyazadeh, S. H. (2021). Punctuality of patients and physicians in an outpatient setting: Which has a greater effect on waiting time? *Hospital Practices and Research*, *6*(3), 112-115. https://doi.org/10.34172/hpr.2021.21

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

Afolalu, S. A., Oladipupo, S., Ongbali, S. O., Abioye, A. A., Abdulkareem, A., Udo, M. O., & Ajayi, O. O. (2020). Queueing theory and index factor for production inventory control in automotive industry—A review. *Lecture Notes in Mechanical Engineering*, 853-860. https://doi.org/10.1007/978-981-15-4745-4_74

Afrane, S., & Appah, A. (2016). Queuing theory and the management of Waiting-time in Hospitals: The case of Anglo Gold Ashanti Hospital in Ghana.

Al-Damen, R. (2017). Health care service quality and its impact on patient satisfaction “case of Al-Bashir Hospital”. https://pdfs.semanticscholar.org/effd/26b4dfca414f4bdf3c8d3998c9b050e23db3.pdf

Bamporiki, T. V., & Bekker, J. (2018). Development of a discrete-event, stochastic multi-objective metaheuristic simulation optimisation suite for a commercial software package. *South African Journal of Industrial Engineering*, *29*(3). https://doi.org/10.7166/29-3-2045

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

Bakker, M., & Tsui, K. L. (2017). Dynamic resource allocation for efficient patient scheduling: A data-driven approach. *Journal of Systems Science and Systems Engineering*, 26(4), 448-462. https://link.springer.com/article/10.1007/s11518-017-5347-3

Banks, J. "Principles of simulation." *Handbook of simulation: Principles, methodology, advances, applications, and practice* (1998): 3-30.

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

Brown, S., Hutton, B., Clifford, T., Coyle, D., Grima, D., Wells, G., & Cameron, C. (2014). A Microsoft-Excel-based tool for running and critically appraising network meta-analyses—an overview and application of NetMetaXL. *Systematic Reviews*, *3*(1). https://doi.org/10.1186/2046-4053-3-110

Carson, John S. "Model verification and validation." *In Proceedings of the winter simulation conference*, vol. 1, pp. 52-58. IEEE, 2002.

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

Cochran, J. K., & Roche, K. (2008). A queuing-based decision support methodology to estimate hospital inpatient bed demand. *Journal of the Operational Research Society*, 59(11), 1471-1482.

Cooper, R. B. (1981, January). Queueing theory. *In Proceedings of the ACM'81 conference* (pp. 119-122). https://dl.acm.org/doi/abs/10.1145/800175.809851

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.

Cuatrecasas-Arbos, L., Fortuny-Santos, J., & Vintro-Sanchez, C. (2011). The Operations-Time Chart: A graphical tool to evaluate the performance of production systems–From batch-and-queue to lean manufacturing. *Computers & Industrial Engineering*, *61*(3), 663-675.

Dehghanimohammadabadi, M., & Keyser, T. K. (2017). Intelligent simulation: Integration of SIMIO and MATLAB to deploy decision support systems to simulation environment. *Simulation Modelling Practice and Theory*, *71*, 45-60. https://doi.org/10.1016/j.simpat.2016.08.007

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.

Greenberg, Craig S., Sebastian Macaluso, Nicholas Monath, Ji-Ah Lee, Patrick Flaherty, Kyle Cranmer, Andrew McGregor, and Andrew McCallum. "Data Structures & Algorithms for Exact Inference in Hierarchical Clustering." *arXiv preprint arXiv:2002.11661* (2020).

Gross, D. (2008). *Fundamentals of queueing theory*. John Wiley & Sons.

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

Huang, W., & Dang, J. (2020). undefined. *Applied Sciences*, *10*(18), 6364. https://doi.org/10.3390/app10186364

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

Huang, X. M. (1994). Patient attitude towards waiting in an outpatient clinic and its applications. *Health Services Management Research*, 7(1), 2-8. https://journals.sagepub.com/doi/abs/10.1177/095148489400700101

Imhoff, M. (2002). Health informatics. *Evaluating Critical Care*, 255-269.

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.

Kuguoglu, S., Aslan, F. E., & Icli, G. (2006). Are patients in Western Turkey contented with healthcare services? A quality assessment study. *Journal of Nursing Care Quality*, 21(4), 366-371.

Lang, S., Reggelin, T., Müller, M., & Nahhas, A. (2021). Open-source discrete-event simulation software for applications in production and logistics: An alternative to commercial tools? *Procedia Computer Science*, *180*, 978-987.

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

Lin, D., Patrick, J., & Labeau, F. (2013). Estimating the waiting time of multi-priority emergency patients with downstream blocking. *Health Care Management Science*, *17*(1), 88-99. https://doi.org/10.1007/s10729-013-9241-3

Lowe, O. (2000). An assessment of patient waiting times at clinics in Tygerberg, Western District in Cape Town, Metropolitan. *Public Health Program, Faculty of Community Health Sciences, University of the Western Cape, Western Cape, South Africa.*

Lynam, P. (1993). COPE: helping to improve the quality of family planning services in Africa. *QA brief*, 2(1), 7-8.

Manggala Putri, A. H., Subekti, R., & Binatari, N. (2017). The completion of non-steady-State queue model on the queue system in Dr. Yap eye hospital Yogyakarta. *Journal of Physics: Conference Series*, *855*, 012034. https://doi.org/10.1088/1742-6596/855/1/012034

Morais Oliveira, M., Marti, C., Ramlawi, M., Sarasin, F. P., Grosgurin, O., Poletti, P., Rouyer, F., & Rutschmann, O. T. (2018). Impact of a patient-flow physician coordinator on waiting times and length of stay in an emergency department: A before-after cohort study. *PLOS ONE*, *13*(12), e0209035. https://doi.org/10.1371/journal.pone.0209035

Murray-Smith, D. J. (2015). Testing and validation of computer simulation models. *Cham: Springer. doi*, 10, 978-3.

Najmuddin, A. F., Ibrahim, I. M., & Ismail, S. R. (2010). A simulation approach: improving patient waiting time for multiphase patient flow of obstetrics and gynecology department (O&G Department) in local specialist centre. *WSEAS Trans Math*, 9(10), 778-790.

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.

Peter, P. O., & Sivasamy, R. (2019). Queueing theory techniques and its real applications to health care systems–outpatient visits. *International Journal of Healthcare Management*.

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.

Rodríguez Jáuregui, G. R., González Pérez, A. K., Hernández González, S., & Hernández Ripalda, M. D. (2017). Análisis del servicio de Urgencias aplicando teoría de líneas de espera. *Contaduría y Administración*, *62*(3), 719-732. https://doi.org/10.1016/j.cya.2017.04.001

Sami R., & Reynolds N. (2021). Medical informatics in neurology: What is medical informatics? Signal processing, image processing. Diseases & Conditions – Medscape Reference. https://emedicine.medscape.com/article/1136989-overview

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

Shakoor, M., Qureshi, M. R., Jadayil, W. A., Jaber, N., & Al-Nasra, M. (2021). Application of discrete event simulation for performance evaluation in private healthcare: The case of a radiology department. *International Journal of Healthcare Management*, 14(4), 1303-1310.

Shalyari, N., Alinejad, A., Hashemi, A. H., RadFard, M., & Dehghani, M. (2019). Health risk assessment of nitrate in groundwater resources of Iranshahr using Monte Carlo simulation and geographic information system (GIS). *MethodsX*, *6*, 1812-1821. https://doi.org/10.1016/j.mex.2019.07.024

Shen, Y., & Lee, L. H. (2020). Improving the wait time to triage at the emergency department. *BMJ Open Quality*, *9*(1), e000708. https://doi.org/10.1136/bmjoq-2019-000708

Shen, Y., & Lee, L. H. (2019). Improving the wait time to admission by reducing bed rejections. BMJ Open Quality, 8(3), e000710.

Sharma, j.k (2013). Operation Research: Theory and Applications. *Fifth edition, Macmillan Publishers LTD*.

Singla, S. (2020). Demand and capacity modelling in healthcare using discrete event simulation. *Open Journal of Modelling and Simulation*, *08*(04), 88-107. https://doi.org/10.4236/ojmsi.2020.84007

Sibanda, L., Engel-Hills, P., & Hering, E. (2017). Radiology demand and capacity: A stochastic analysis based on care pathways. *Cogent Business & Management*, *4*(1), 1334994. https://doi.org/10.1080/23311975.2017.1334994

Takagi, H., Kanai, Y., & Misue, K. (2016). Queueing network model for obstetric patient flow in a hospital. *Health Care Management Science*, *20*(3), 433-451. https://doi.org/10.1007/s10729-016-9363-5

Torabigoudarzi, H. (2019). *Modeling and simulation of emergency radiology unit at St. Paul's Hospital* (Doctoral dissertation, University of British Columbia).

Tlapa, D., Zepeda-Lugo, C. A., Tortorella, G. L., Baez-Lopez, Y. A., Limon-Romero, J., Alvarado-Iniesta, A., & Rodriguez-Borbon, M. I. (2020). Effects of lean healthcare on patient flow: A systematic review. *Value in Health*, *23*(2), 260-273. https://doi.org/10.1016/j.jval.2019.11.002

Vázquez-Serrano, J. I., Peimbert-García, R. E., & Cárdenas-Barrón, L. E. (2021). Discrete-event simulation modeling in healthcare: A comprehensive review. *International Journal of Environmental Research and Public Health*, *18*(22), 12262. https://doi.org/10.3390/ijerph182212262

Xu, K., & Chan, C. W. (2016). Using future information to reduce waiting times in the emergency department via diversion. *Manufacturing & Service Operations Management*, *18*(3), 314-331. https://doi.org/10.1287/msom.2015.0573

Yancey, C. C., & O'Rourke, M. C. (2021). Emergency Department Triage. *StatPearls [Internet]*. https://www.ncbi.nlm.nih.gov/books/NBK557583/

Yaduvanshi, D., Sharma, A., & More, P. V. (2019). Application of queuing theory to optimize waiting time in hospital operations. *Operations and Supply Chain Management: An International Journal*, 165-174. https://doi.org/10.31387/oscm0380240

Yazbeck, M. I. (2018). Simulating patient flow at the LAUMC Radiology Department (Doctoral dissertation)

Zhang, L. (2020). Application of computer-based queuing theory in public hospital management. *Journal of Physics: Conference Series*, *1549*(5), 052009. https://doi.org/10.1088/1742-6596/1549/5/052009