A MONTE CARLO SIMULATION TO SUPPORT DECISION MAKING IN REDUCING OUTPATIENT CLINIC WAITING TIME

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DECLARATION

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

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ABSTRAK

Disebabkan peningkatan lawatan pesakit, sebuah hospital di Lembah Klang sedang mencari cara untuk meningkatkan kepuasan pesakit dan menggunakan sumber yang ada dengan lebih berkesan. Masa menunggu pesakit telah ditentukan sebagai KPI utama untuk penyiasatan ini. Dalam kajian ini, kesan ramalan masa perkhidmatan yang dibuat menggunakan teknik perlombongan data terhadap masa menunggu pesakit dan masa temujanji telah disiasat. Dengan menggunakan simulasi Monte Carlo berasaskan baris gilir penyelidikan operasi dalam alat sokongan keputusan berasaskan hamparan, penyelidik dapat mengkaji kesan memperuntukkan jenis pesakit tertentu kepada jadual baharu untuk pesakit di jabatan. Prinsip teori beratur telah digabungkan dalam model. Selain itu, ia meningkatkan skop simulasi acara diskret untuk menggabungkan masa perkhidmatan dan kadar ketibaan pesakit. Model simulasi juga digunakan untuk membina dan menganalisis sistem giliran jabatan. Alat sokongan keputusan kini menggunakan model ramalan. Dengan mencipta alat ini, masa menunggu keseluruhan sistem akan diperiksa untuk memahami cara mengubah suai komponen sistem tertentu akan mempengaruhinya. Keputusan simulasi menunjukkan bahawa pengurusan sistem beratur yang lemah,dan bukannya kekurangan sumber. Hasil daripada simulasi menunjukkan bahawa pengurangan purata keseluruhan masa menunggu di jabatan daripada 37.24 minit kepada 29.22 minit semasa waktu perniagaan adalah mungkin dengan menjangkakan masa perkhidmatan dengan tepat dan memperuntukkan pesakit kepada slot masa tertentu. Dengan penggunaan alat sokongan keputusan, pendekatan pemodelan ini boleh memaklumkan para eksuketif kesihatan secara berkesan tentang keberkesanan sistem temujanji berperingkat pada masa menunggu pesakit.

ABSTRACT

Due to an increase in patient visits, A hospital in the Klang Valley is looking for ways to enhance patient satisfaction and utilize available resources more effectively. Patient waiting times were determined as the primary KPIs for this investigation. In this study, the effects of service time predictions made using data mining techniques on patient waiting times and appointment times were investigated. By employing an operational research queue-based Monte Carlo simulation in a spreadsheet-based decision support tool, researchers are able to examine the effects of allocating a certain type of patient to a new schedule for patients in the department. Queuing theory's tenets were merged in the model. Additionally, it increased the scope of the discrete event simulation to incorporate service time and patient arrival rates. The simulation model was also used to build and analyze the department queue system. The decision-support tool now uses the prediction model. By creating this tool, the system's overall waiting time will be examined to understand how modifying certain system components will affect it. The results of the simulation suggest that poor queuing system management, rather than a lack of resources, is the fundamental issue. Results from the simulation showed that reducing overall average waiting times in the department from 37.24 minutes to 29.22 minutes during business hours was possible by precisely anticipating the service time and allocating patients to a certain time slot. With the use of a decision support tool, this modelling approach could effectively inform healthcare decision-makers about the effects of optimizing the current staggered appointment system on patient wait times.

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CHAPTER I

INTRODUCTION

1.1 OVERVIEW

The provision of outstanding services is a major goal for firms in the healthcare sector. Healthcare companies work hard to deliver high quality treatment, ensuring that patients get the immediate, effective care they require. Effectively controlling patient wait times in clinics is a critical component of providing great services(Sundresh,2017).The term "waiting time" describes how long a patient must wait in the outpatient area before being seen by a member of the clinic's medical staff. Waiting times are a significant aspect in healthcare settings that influence both patient happiness and the effectiveness of healthcare delivery. In hospitals or specialised clinics, patients may have to wait a long time before receiving the required services. The length of time a patient must wait at a hospital or other medical facility before obtaining services is referred to as the wait time. High patient wait times in clinics are a persistent problem that affects managers and medical staff(Egbujie et al., 2018).

1.2 PROBLEM BACKGROUND

Longer patient wait times in clinics are a serious concern in medical settings. It not only has a detrimental effect on patient satisfaction, but it also poses difficulties for management and healthcare professionals. Long wait times frequently cause patients to lose patience, which can result in irritation with a sense of subpar care(Egbujie et al., 2018). Long wait times are a major factor in patients' unhappiness at healthcare facilities, which poses problems for managers and healthcare professionals.(Egbujie et al., 2018). In most healthcare settings, research has also revealed a negative link between waiting times and patient satisfaction.(Egbujie et al., 2018).

Patients' opinions on the waiting time at the medical office can have a big impact on how happy they are with the care they receive. Long waiting times are also thought to pose a serious threat to the public's confidence in the healthcare system as they are a significant contributor to dissatisfaction with hospitals and other healthcare providers (Hashemi et al., 2017). To increase patient satisfaction, raise overall care quality, and preserve faith in the healthcare system, this problem must be resolved. The length of time patients wait for services has a significant impact on their experiences in healthcare facilities. Long waiting times for appointments at clinics can make patients unhappy and have a detrimental effect on how well they are treated. Furthermore, wealthy nations are not the only ones who experience long patient wait times in clinics. It is also common in developing nations, where little funding, poor healthcare service organisation, and high patient-to-doctor ratios cause lengthy wait times and low satisfaction(Afe et al., 2016). The issue of high patient clinic waiting time is deemed significant and has wide-ranging implications(Egbujie et al., 2018). It not only affects patient happiness and faith in the healthcare system, but it also presents difficulties for management and healthcare professionals. A comprehensive strategy including a range of stakeholders, including healthcare administrators, policymakers, healthcare providers, and patients themselves is needed to address the issue of long patient wait times in clinics. Healthcare organisations must understand how critical it is to control patient wait times in clinics and take action to do so. Healthcare companies may significantly decrease patient wait times in clinics and raise patient satisfaction by putting into practise initiatives including streamlining workflows, expanding staff capacity, and optimising scheduling processes. Healthcare organisations can enhance the overall quality of care and uphold public confidence in the healthcare system by tackling the issue of long patient wait times in clinics. (Hashemi et al., 2017). The overall quality of care and patient happiness are negatively impacted by long wait times in clinics, which is a serious issue.

1.3 PROBLEM STATEMENT

A patient's wait time for services in a hospital or specialty clinic can change based on several variables, including the number of patients, the accessibility of medical professionals, the effectiveness of administrative procedures, and the sufficiency of resources. Patient satisfaction and waiting times have an inverse connection in the majority of healthcare settings(Egbujie et al., 2018). If patients must wait a lengthy time before receiving the necessary care, they are more likely to be dissatisfied with their experience(Egbujie et al., 2018). High patient wait times in clinics is a serious issue since it affects patient satisfaction and has larger ramifications for managers and healthcare professionals(Egbujie et al., 2018). Patient dissatisfaction at healthcare facilities is largely a result of long wait times at clinics, which is problematic for managers and healthcare professionals. Both patients and healthcare organisations are impacted by this problem. Due to lengthy wait times, patients who visit healthcare institutions frequently express high levels of discontent. This unhappiness may result in poorer compliance rates and a poor opinion of the care's quality.

Additionally, healthcare companies that find it difficult to control and lower patient wait times in clinics may experience reputational concerns, a decline in patient confidence, and even legal repercussions. Additionally, evidence from numerous research shows that lengthy wait times have a detrimental influence on patient satisfaction. For instance, a study done in the USA indicated that low rates of compliance and significant patient dissatisfaction with long wait times to see a doctor led to poor compliance. Similarly, a 1992 British study found that long wait times are seen as a healthcare barrier and that patient satisfaction is directly correlated with clinic wait times. There are no nation or healthcare systems where this issue only exists. It is a global problem that has an impact on people and medical professionals everywhere. High clinic wait time have effects that go beyond just patient pleasure.

Hospitals have tried a range of techniques to address the issue of reducing patient waiting times, acknowledging the significance of this matter. A commonly employed tactic is the adoption of an expedited methodology, whereby individuals seeking medical attention are promptly evaluated and attended to upon their arrival. The objective of this strategy is to optimize the efficiency of patient flow and reduce waiting time. An alternative methodology involves the application of queuing analysis, as exemplified by Mital's investigation on the assessment of service quality inside a hospital setting in India. The present study encompassed the assessment of many factors, including the mean duration of patient waiting, the average length of the queue, and the occurrence of both prolonged and brief delays. These tactics have the potential to offer significant insights into the factors that contribute to bottlenecks in patient waiting time and can inspire focused interventions aimed at reducing waiting times. Nevertheless, notwithstanding these endeavors, numerous obstacles exist in the quest for a resolution to mitigate patient waiting duration.

Multiple case studies have demonstrated effective strategies for reducing patient wait times. In Australia, a research was conducted to address the issue of lengthy waiting times for surgical procedures. The study introduced a specific intervention in the form of a specialised position known as the "surgery access manager" to oversee and streamline the process of accessing surgical services. The manager assumed the responsibility of coordinating and optimising surgical schedules, prioritising urgent cases, and ensuring the effective utilisation of operating room resources. The intervention yielded noteworthy outcomes, as evidenced by the study's findings which indicated a substantial decrease in surgical waiting times and enhanced levels of patient satisfaction. In a similar vein, research conducted in New Zealand included a centralised referral system aimed at optimising the process of directing patients to specialised healthcare facilities. The implementation of this system facilitated enhanced coordination and communication, resulting in decreased waiting periods and enhanced availability of healthcare services. A wait list management system was introduced in England, wherein patients were prioritised according to their clinical need and level of urgency. The study conducted by Barber et al. (2015) discovered that the implementation of this approach resulted in a notable reduction in waiting times for specialised care and a more efficient utilisation of healthcare services. The Effects of Prolonged Waiting Periods on Patients and the Healthcare System The imperative goal for healthcare practitioners is to minimise patient waiting time due to the adverse consequences it can have on both patients and the healthcare system (Batubara et al., 2020).

1.4 ANALYZING THE PROBLEM

Extended clinic wait times might result from several different things. These consist of:

1. Insufficient staffing levels can result in lengthier wait times since there may not be enough medical professionals to treat every patient as quickly as necessary.

2. Limited physical space in healthcare facilities can lead to crowding and lengthier patient wait times for ambulatory services.

3. Poorly scheduled appointments may be a result of ineffective scheduling techniques, such as double booking or not allocating enough time for each patient.

4. Delays in the triage process that patients may have to wait longer if the initial evaluation and prioritisation of patients are not done correctly.

5. Service delivery delays in clinics can be caused by bottlenecks in the healthcare system, such as a delay in test results, consultations, or procedures.

Patient wait times can increase as a result of time-consuming administrative chores like paperwork and registration. High patient demand might result in longer wait times since healthcare professionals may find it difficult to accommodate and treat every patient as soon as they arrive at the clinic.

1.5 PROBLEM IMPLICATIONS

Longer patient wait times have many effects that can affect all facets of healthcare. There is still more to learn about the financial impact of long wait times. Longer wait times can cost patients more money in the form of transportation costs, lost pay from time away from work, and higher healthcare expenditures if the disease worsens because of the delay in receiving care. Long patient wait times may also be detrimental to the general effectiveness and operations of healthcare institutions. Long wait times at clinics may result in a greater need for physical resources, such as extra room or staff, to handle the influx of patients and clear backlogs. Due to the increased demand for resources, healthcare budgets and resources may be strained, which could result in inefficiencies and delays in other aspects of healthcare delivery.

1.5.1 Patient's perspective

Patients who wait a long time at the clinic may suffer from a variety of unfavourable effects. Long wait time at the doctor's office or clinic can frustrate patients and negatively affect their experience with the medical system. In addition to the inconvenience of having to wait a long period, patients could feel physically and mentally uncomfortable. Long durations of standing or sitting in a busy waiting area can be physically taxing, especially for patients with mobility problems or diseases that cause persistent discomfort. Additionally, long wait times can cause anxiety and stress, both of which can be harmful to the mental health of patients. Patients may feel frustrated and helpless because they believe their time is being spent and that their essential medical demands are not being met. As a result, patients may be less likely to adhere to clinic appointments and treatment plans because they may lose faith in the clinic's capacity to promptly address their needs and grow disenchanted with the healthcare system.

1.5.2 Perceived discrimination and financial burden

Longer wait times in clinics can make patients feel discriminated against in addition to their physical and mental suffering. Patients who must wait longer than expected for visits or who have had their appointments delayed may feel stigmatised and think they are being punished for skipping or rescheduling appointments. (Peer et al., 2020). Furthermore, it's important to consider the financial costs of long patient wait times in clinics. Patients may incur additional fees for transportation and childcare as a result of prolonged wait periods. They might have to take time off work or plan for substitute childcare, which would put additional financial strain on people and families who are already struggling financially. Therefore, the issue of long wait times at clinics impacts patients' adherence to appointments and treatment plans as well as the efficiency and resource allocation of healthcare providers. It also affects patients' perceptions of discrimination and the financial burdens they must bear. (Peer et al., 2020).

1.5.3 Resource strain to healthcare

Longer patient clinic wait times can have a substantial impact on how healthcare facilities operate and how they use their resources. Longer patient wait times frequently lead to a rise in the need for medical staff and ambulatory care facilities. To handle the rising patient volume and shorten wait times, clinics may need to increase staff or extend their hours. Due to the increased demand for resources, healthcare budgets and resources may be strained, which could result in inefficiencies and delays in other aspects of healthcare delivery. Longer patient wait times in clinics have an adverse effect on physicians that extends beyond resource depletion. Longer wait times for patients may also result in higher rates of missed appointments, which would result in inefficient appointment scheduling and lower throughput for the clinic (Peer et al., 2020). This could exacerbate wait times and set off a cycle of greater waits and missed appointments.

Long clinic wait times for patients are a complicated problem that has an impact on a variety of parties, including patients, medical staff, and the healthcare system. This issue is most evident in specialist clinics, where greater wait times and missed appointments have received less research. This emphasises the requirement for additional analysis and solutions to the issue of lengthy patient wait times in clinics. High patient wait times in clinics are a major hindrance to providing the best possible care and have a detrimental effect on patient compliance, the standard of care, and patient happiness. Additionally, prolonged wait times may have a negative impact on patients' health, particularly in geriatric populations where longer wait times have been linked to higher mortality rates.

Prolonged patient wait times in clinics have consequences for the entire healthcare system in addition to having a negative effect on patients and healthcare professionals. Due to the necessity for extra appointments and treatments because of missing or delayed care, prolonged waiting periods raise the expense of healthcare. A topic that needs more research is the financial burden that long patient wait times in clinics have on the healthcare system.

1.6 RESEARCH QUESTIONS

Multiple studies have suggested that a crucial element in the provision of a simulation model involves effectively showcasing the performance of a healthcare facility. This is achieved by accurately representing the existing system processes and establishing a foundation for enhancing these processes inside the system. Healthcare environments are essentially characterised by diversity and complexity, as they comprise a broad spectrum of specialisations, departments, and services. The presence of distinct workflows, processes, and protocols in each healthcare setting poses challenges in developing a standardised model for performance evaluation, as generalisation becomes intricate. Moreover, the dynamic and unexpected nature of patient flow introduces an additional level of intricacy. The circumstances, needs, and treatment requirements of patients might exhibit considerable variation, resulting in a corresponding fluctuation in the time and order of workflow activities. Furthermore, the incorporation of several healthcare departments and providers adds complexity to the modelling procedure. To effectively model medical processes, it is vital to take into account certain essential data parameters. The acquisition and examination of requisite data parameters are imperative in the creation of authentic time series datasets and the formulation of precise forecasts.

Various strategies have been proposed to enhance the efficiency of healthcare appointment scheduling, encompassing dynamic scheduling algorithms, data analytics, and technological interventions. One approach to enhance the efficiency of healthcare appointment scheduling is the utilisation of data analytics. The utilisation of data analytics in the healthcare sector enables healthcare practitioners to examine past appointment data, patient preferences, and resource availability to discern recurring patterns and emerging trends. Through the analysis of this data, healthcare providers can make well-informed decisions regarding scheduling. The utilisation of data analytics in the healthcare industry enables providers to make accurate predictions regarding future demand and then change scheduling practises to optimise resource allocation.

1.7 RESEARCH OBJECTIVES

The main goal of this dissertation is to propose a solution to reduce patient clinic waiting time using computer science knowledge and domain knowledge. This goal will be achieved by extracting and analyzing the obtained queue system data from the cardiology department with the following objectives:

1. To develop a model that closely replicates the current queue system

2. To propose a new queue model for the cardiology department that reduces the overall patient waiting time.

1.8 SCOPE OF STUDY

The study falls under the Health Informatics domain which is about using computational techniques to solve problems faced by the healthcare industry. This dissertation focuses on searching for the accurate tools to use to solve the queueing problem. The machine learning models that will be used in the study encompass predictive and prescriptive analysis along with appreciating the queue theory mathematical model. The results of the analysis will be used in creating a simulation model and a new proposed model will be developed. Lastly the performance of the mentioned developed model will be benchmarked with the original data collected. A detailed explanation of the research methods involved will be explained in the following chapter.

1.9 CONCLUSION

Healthcare enterprises ought to adopt a holistic strategy that integrates various methodologies and technology in order to mitigate patient clinic waiting durations. The implementation of proactive measures such as process modelling, staff training, and the application of healthcare business strategies can enhance clinic operations, improve patient satisfaction, and ultimately provide high-quality healthcare services. In summary, the reduction of extended waiting periods in healthcare facilities is crucial for improving patient satisfaction and overall healthcare quality. According to the study conducted by Kshatri et al. (2017), Healthcare enterprises ought to consider adopting a comprehensive strategy that integrates many methodologies and technology to effectively manage extended patient waiting periods within clinics. This involves enhancing communication, optimising patient flow, improving online appointment scheduling, using telemedicine, prioritising care for vulnerable populations, and utilising management tools and automated prioritisation systems. By implementing these strategies, outpatient clinics can enhance their overall productivity and achieve lower waiting times, leading to increased patient satisfaction. The integration of management software and automated prioritising systems into the daily operations of healthcare firms has the potential to significantly reduce waiting times and enhance the efficiency of outpatient clinics.

CHAPTER II

LITERATURE REVIEW

2.1 INTRODUCTION

In the contemporary era of digital advancements, technology assumes a crucial function in the reduction of patient waiting durations. A successful approach involves the establishment of a Hospital Examination Reservation System that relies on Health Information Systems and Picture Archiving and Communication Systems. The implemented method facilitates patients in scheduling appointments and securing preferred time slots in advance, hence mitigating the necessity for enduring extended lineups. Moreover, the system aids in the optimisation of the scheduling process through the effective allocation of resources and the mitigation of overbooking or double-booking occurrences. An additional technical approach involves the implementation of centralised intake systems that integrate single-entry models with wait list management (Barber et al., 2015).

Empirical evidence has demonstrated the efficacy of these systems in mitigating waiting periods for specialised medical attention and enhancing the overall use of healthcare resources. Nevertheless, notwithstanding the progress made in technological improvements and the adoption of diverse tactics, there persist some obstacles in the quest for a resolution to mitigate patient waiting duration. One of the primary obstacles encountered pertains to the constraints on capacity within healthcare systems. Healthcare facilities frequently have constraints in relation to the quantity of healthcare experts, equipment, and infrastructure at their disposal to adequately address the demand for services. The constraint on capacity is a notable obstacle in the endeavour to decrease patient waiting periods, as there may be insufficient resources available to promptly attend to all patients. One additional obstacle in the endeavour to decrease patient waiting time is the presence of inconsistent wait times across various healthcare providers within a given geographical region. The observed diversity can be ascribed to multiple reasons, encompassing disparities in the distribution of resources, efficiency within the organization, and variations in the patient group.

Moreover, the absence of effective coordination and communication among diverse healthcare professionals can give rise to inefficiencies within the overarching system, hence leading to extended waiting periods for patients. One additional obstacle encountered in the endeavour to decrease patient waiting time is the prevailing reluctance to embrace change within the healthcare sector. Healthcare systems exhibit a high degree of complexity and frequently demonstrate a reluctance to embrace change, which can be attributed to a multitude of causes such as bureaucratic frameworks, well-established protocols, and opposition from healthcare practitioners. Furthermore, the presence of financial limitations might also present a formidable obstacle in the pursuit of identifying a viable resolution to decrease patient waiting periods.

The financial limitations experienced by healthcare systems can impede their capacity to allocate resources towards technological advancements and infrastructural enhancements, which have the potential to mitigate patient waiting times. In addition, the resolution of patient waiting time necessitates a comprehensive strategy that entails the cooperation and synchronization of several actors, such as healthcare professionals, administrators, lawmakers, and patients themselves. One potential strategy for enhancing patient flow and minimizing waiting times is to enhance collaboration and communication among healthcare practitioners. Furthermore, the integration of technological solutions, such as appointment scheduling systems, electronic health records, and telemedicine, can effectively enhance the allocation of resources and enhance the efficiency of healthcare delivery.

2.2 CHALLENGES AND SOLUTIONS

Limited resources, staff, equipment, and space are sometimes few in healthcare institutions. Longer wait times and crowding due to a lack of resources can have a negative effect on patient satisfaction and the standard of care. By using queue management techniques, this problem can be solved. Methods of queue management aid in resource allocation optimization and improve patient flow. These techniques may include waiting time tracking in real-time, appointment scheduling, and triage systems.

Patient demand in healthcare can be very unpredictable, making queue management and forecasting challenging. The application of queueing theory provides a solution to this problem. Healthcare facilities can better predict peak demand periods and distribute resources accordingly by using queueing theory to examine and predict patient demand patterns(Marcikić et al., 2016). There are various advantages to using queue management techniques and decision support systems together in healthcare. These consist of:

1. Efficiency gain: Decision support systems can help medical professionals make decisions more quickly and accurately, which will result in more effective patient care.

2. Enhanced patient happiness: Queue management techniques can reduce wait times and streamline the patient experience, both of which will raise satisfaction levels.

3. Improved adherence to evidence-based recommendations and decreased medical errors are two factors that can contribute to decision support systems' ability to increase patient safety.

Healthcare decision support systems that are accurate and fast can lead to better patient outcomes and lower costs. Finally, the use of queue management techniques and decision support systems in healthcare can help with issues like scarce resources and fluctuating patient demand. This integration might boost productivity, increase patient satisfaction and safety, and eventually result in improved patient outcomes and lower healthcare costs.

These technologies give healthcare professionals relevant data and insights that aid in decision-making and efficient resource allocation. Additionally, the use of computerised queuing systems might take the place of manual ones, resulting in more effective queue management in healthcare institutions. (Choosri et al., 2022). These systems can examine patient data and produce statistical reports, giving important insights into present and upcoming flow trends. To successfully control patient flow and reduce wait times, healthcare companies must use queue management techniques(Choosri et al., 2022). Healthcare businesses can streamline their procedures and boost overall system effectiveness by employing precise and effective queue management techniques. In conclusion, integrating decision support systems and queue management techniques in healthcare might help overcome issues like scarce resources and fluctuating patient demand. Through this integration, productivity may be increased, patient happiness and safety can be improved, and better patient outcomes can result in lower healthcare expenditures.

2.3 QUEUE MANAGEMENT METHODS

Another crucial component of providing healthcare is managing lines of patients. The term "queue management" describes the techniques and plans employed in healthcare settings to effectively control patient flow and shorten wait times. Healthcare businesses are implementing queue management technology to solve this problem. In healthcare settings, queue management techniques are used to shorten the patient experience and maximise resource allocation. Healthcare facilities can minimise patient wait times, raise patient satisfaction levels, and make the best use of their available resources by employing effective queue management techniques. Appointment scheduling systems are a typical queue management technique used in healthcare settings. The need for patients to wait in long lines is reduced by appointment scheduling systems that enable patients to make their appointments in advance. Additionally, by assisting healthcare professionals in more efficient time and resource management, appointment scheduling systems guarantee that patients are seen on time. In healthcare contexts, triage is another approach to queue management. According to the seriousness of their condition, patients are prioritised throughout the triage procedure. This enables medical professionals to distribute resources effectively and guarantee that patients with lifethreatening diseases receive prompt attention. The use of queue management techniques in healthcare settings has many advantages. Additionally, to enhancing patient satisfaction and safety, it also raises the general effectiveness and efficiency of healthcare organisations.

2.3.1 Efficiency improvement

Efficiency in healthcare environments can be greatly increased by using queue management techniques. These techniques can be used by healthcare facilities to shorten wait times and streamline the patient experience. This can be accomplished using a variety of tactics, including electronic queuing systems, triage systems, and appointment scheduling systems. The possibility of lengthy waiting times is decreased when healthcare institutions use appointment scheduling systems to assign patients to precise time windows.

In order to ensure that individuals who require urgent treatment receive it in a timely manner, triage systems can help prioritise patients based on the severity of their conditions. Electronic queuing systems can minimise ambiguity and annoyance by giving patients real-time updates on wait times and alerting them when it is their turn.

2.4 DECISION SUPPORT SYSTEMS

Decision support systems, or DSS for short, are technology tools that help medical personnel make defensible choices about the care of their patients. To provide clinical advice and support the decision-making process, these systems collect and analyse data from diverse sources, including electronic health records and medical literature. Because of advancements in software and computer technology, the use of decision support systems in healthcare has become crucial and important(Mostaar et al., 2019). These solutions aid in reducing diagnostic time and enhancing diagnosis precision, which eventually improves patient outcomes.

Clinical decision support systems are one type of decision support system used in healthcare. These interactive computer applications were created with the express purpose of helping doctors and other healthcare professionals make clinical judgments

(Mostaar et al., 2019). Based on information particular to each patient, clinical decision support systems offer real-time direction and evidence-based suggestions to healthcare professionals. Clinical decision support systems can help to improve healthcare services, according to research, and their deployment can help.

2.4.1 Decision support systems in healthcare

By offering useful data and insights to support decision-making processes, decision support systems play a significant role in the healthcare sector. The utilisation of exact and timely data, information, and knowledge management is a key component of these systems' design, which aims to promote precise decision-making. Clinical decision support systems, a particular kind of decision support system, are used in the healthcare sector. Systems for making clinical decisions are connected to electronic health data and are specifically designed for the healthcare environment. By providing pertinent, organised clinical knowledge and patient information, these systems improve health-related decisions and activities. Clinical decision support system integration with electronic health records has been shown to enhance patient safety, healthcare delivery effectiveness, and overall quality of care. Clinical decision support systems' capacity to filter and process data entered by healthcare professionals is one of its main advantages. Clinical decision support systems enable healthcare professionals to make well-informed choices about patient care based on a pre-defined set of rules and data incorporated in the system. These decision support systems are capable of enhancing the efficiency of cost-effective care, enhancing the quality of care and outcomes, and preventing errors by utilising the data and knowledge contained in the system.

2.4.2 Impact of decision support

The application of decision support tools in the medical field has the potential to have a significant impact on patient care. By reducing errors and boosting the effectiveness of care that is cost-effective, these systems can increase the quality of treatment and results. Decision support systems, for instance, can aid medical professionals in providing quicker and more accurate diagnoses. Decision support systems can recommend potential diagnoses and treatment choices by assessing patient data and comparing it to a predefined set of criteria and information stored in the system.

2.4.3 Practical applications in medicine

Medical practise includes the following practical applications of decision support systems:

1. Clinical decision support systems: By offering evidence-based suggestions and alerts, these systems help healthcare practitioners make clinical decisions. The best practises, clinical guidelines, and potential errors can all be followed by physicians with the aid of these suggestions and alerts.

2. Systems for supporting diagnostic decisions: These tools assist medical professionals in the diagnosis process by examining patient information, symptoms, and medical background to generate a list of potential diagnoses or recommendations for more testing(Mostaar et al., 2019).

2.4.4 Optimizing healthcare delivery

By giving clinicians the resources and knowledge they need to make wise judgments, decision support systems play a critical part in improving the delivery of healthcare. These systems examine patient data using algorithms and data analysis to suggest diagnoses and treatments. Decision support systems can decrease errors, raise the standard of care, and enhance patient outcomes by aiding doctors in making decisions. Additionally, decision support tools can help clinicians manage their time effectively. Decision support systems can assist physicians in prioritising their work and scheduling their time more effectively by automating some tasks and giving them access to pertinent information.

2.5 INTERSECTION OF DECISION SUPPORT SYSTEMS AND QUEUE MANAGEMENT IN HEALTHCARE

Even higher gains in effectiveness and patient happiness may result from the fusion of queue management and decision support systems in healthcare. Healthcare administrators can access real-time analytics through the use of decision support systems, which can collect data from queue management systems. This can assist in forecasting demand, locating patient flow bottlenecks, and allocating resources appropriately. Healthcare facilities can optimise the patient experience and shorten wait times by combining decision support systems with queue management techniques. With timely care for patients and resource optimization for healthcare professionals, an integrated healthcare system may be more effective and efficient. Both patients and providers may be significantly impacted by these advancements in healthcare delivery.

2.6 MONTE-CARLO TECHNIQUE

Healthcare companies can use the Monte Carlo method and queueing theory to reduce patient wait times in clinics. Queueing theory is a mathematical method for analysing how waiting lines or queues behave. Reducing the amount of time spent in lines by implementing queueing theory in healthcare companies will increase staff and patient satisfaction(Marcikić et al., 2016 The typical organisational issue in many healthcare organisations is that the amount of people on hand was decided ad hoc without taking demand or system load into account(Marcikić et al., 2016). The effectiveness of the overall healthcare system may be harmed by this disregard for demand and system strain. Healthcare businesses can successfully control patient clinic wait times by allocating the right number of staff members by precisely assessing demand and system load using queueing theory(Marcikić et al., 2016). The optimization of patient wait times in clinics can be further improved by using the Monte Carlo technique in conjunction with queueing theory. The Monte Carlo technique uses mathematical simulations and random sampling to model numerous scenarios and identify the most effective ways to shorten wait times.

This method may account for variables such as patient arrival and service times, their unpredictability, and the level of inventory, which includes the number of individuals in the waiting area and the number of people who receive service. Healthcare companies can simulate numerous scenarios and assess the effects of various tactics on patient clinic wait times by using the Monte Carlo technique. Healthcare businesses can reduce outpatient waiting times and boost work efficiency by fully identifying the best scheduling approach and utilising resources possible. Queuing issues may occur in healthcare organisations because of mismatches between the quantity of consumers and available service facilities.

By controlling the queue well, queueing theory can be used to reduce patient waiting times in healthcare facilities(Marcikić et al., 2016). This can be achieved by streamlining the staffing plan and assigning the right number of employees in accordance with system load and demand. In addition, other industries including small enterprises, supermarkets, subway stations, ticket booths, and multi-stage production lines can gain from the use of queueing theory in healthcare organisations. Additionally, the optimization of diverse processes and decision-making in many industries is possible with the help of the Monte Carlo simulation approach and queueing theory. A useful tool for reducing patient wait times in clinics is the queueing theory in combination with the Monte Carlo simulation technique.

The concept of Queuing theory of operation research has been applied to reduce the patients waiting time by applying Monte Carlo modelling method (Hussain & Hussain, 2019). To manage and control the patients waiting list of radiotherapy treatment, optimal scheduling strategy have been introduced (Hussain & Hussain, 2019). The common organisational issue in many healthcare companies is that the number of staff members is set ad hoc, regardless of demand and system load, which could have a negative impact on the system's overall efficiency(Marcikić et al., 2016). Inadequate matches between clients and service facilities can also result in a queuing problem, necessitating the application of queue theory to reduce wait times(Debebe & Demiss, 2022).

A previous study demonstrated how queueing theory and the Monte Carlo simulation method were applied to optimize various industries, including small businesses, healthcare, supermarkets, subway stations, ticket windows, and multi-stage production lines(Debebe & Demiss, 2022).In the optimization of call center staffing, transportation of sugar cane to mills, and the development of ranked checklists for risk assessment, the Monte Carlo simulation method was also utilized in conjunction with queueing theory(Debebe & Demiss, 2022).

To improve the effectiveness of a system and enhance decision-making, the application of queueing theory in healthcare and other industries can provide valuable insights(Šprajc et al., 2017). The importance of effectively matching the workforce to demand and system load cannot be emphasised in today's world of fast change. The use of queueing theory and the Monte Carlo simulation approach in a variety of industries has shown to be beneficial in streamlining procedures and cutting down on wait times in today's environment of rapid change. Patient clinic wait times have been successfully optimised in healthcare organisations using queueing theory and the Monte Carlo simulation technique. Healthcare companies may efficiently manage and control patient waiting lists, apply the best scheduling practises, maximise resource utilisation, and minimise outpatient waiting times by employing queueing theory and the Monte Carlo simulation method(Hussain & Hussain, 2019). Furthermore, the application of queueing theory in healthcare organizations can address the common problem of staff allocation(Marcikić et al., 2016). This issue frequently occurs when the amount of personnel resources is chosen at random, without taking demand or system load into account. By using queueing theory, healthcare companies can decide on staffing levels with knowledge, leading to increased effectiveness and satisfaction for both patients and staff(Marcikić et al., 2016).

In summary, optimising patient wait times in clinics has been made possible using the Monte Carlo simulation approach and queueing theory in healthcare organisations. It enables companies to execute ideal scheduling techniques, better manage and regulate patient waiting lists, make the most of their resources, and cut down on outpatient waiting times. In addition, it has been shown that the application of queueing theory and the Monte Carlo simulation technique is efficient in a variety of fields outside of healthcare, including small business operations, transportation, and telecommunications.

Overall, the use of queueing theory and the Monte Carlo simulation technique in the healthcare and other industries provides insightful information and practical suggestions for streamlining procedures, cutting wait times, and enhancing system effectiveness. The optimization of patient wait times in clinics has shown promise when queueing theory and the Monte Carlo simulation method are used. (Hussain & Hussain, 2019).

2.7 UNDERSTANDING PRESCRIPTIVE ANALYTICS

A potent tool for producing suggestions for decisions, prescriptive analytics combines descriptive and predictive analytics. It goes beyond merely forecasting outcomes and goes one step further by recommending the optimal course of action to bring about a desired result.

Advanced mathematical models, algorithms, and optimization strategies are used to achieve this. Prescriptive analytics seeks to enhance decision-making by taking into account a range of restrictions, goals, and uncertainties. Organizations can make better, data-driven decisions and improve efficiency, cost savings, and operational success by implementing prescriptive analytics into a business model. Prescriptive analytics has become increasingly popular in the era of "big data" because it makes use of the large amount of information at its disposal to offer useful insights. Prescriptive analytics offers guidance on potential outcomes and remedies using optimization and simulation methods(Yange et al., 2020). Based on input and data-mining techniques, these algorithms examine data from various sources and identify the best course of action.

2.7.1 Optimization techniques

Among the essential elements of prescriptive analytics is optimization, which entails selecting the ideal answer from a range of workable choices. To find the best course of action that maximises desired outcomes or reduces costs or risks, optimization approaches use mathematical models and algorithms. Prescriptive analytics optimization strategies consider a variety of restrictions, such as restricted resources or budget constraints, to discover the most practical and efficient solution. From workforce scheduling and supply chain management to financial portfolio optimization and production planning, these strategies can be used in a variety of contexts. Prescriptive Analytics using Stochastic Modelling An additional crucial element of prescriptive analytics is stochastic modelling. To reflect the variability and potential risk in decision-making processes, it entails introducing randomness and uncertainty into mathematical models. Stochastic models assess and quantify uncertainty in numerous elements of the decision-making process using probability theory and statistical methodologies. These uncertainties may be caused by variables like changes in market demand, bad weather, or malfunctioning machinery. Optimization methods and stochastic modelling are combined in prescriptive analytics to produce more reliable and precise decision-making solutions. Prescriptive analytics supports companies in making knowledgeable decisions that are not only effective but also robust in the face of uncertainty by taking into account both the ideal solution and the potential risks and uncertainties(Yange et al., 2020). Utilizing optimization approaches, prescriptive analytics chooses the optimum course of action among several possibilities while taking into account a variety of limitations and goals.

2.7.2 Stochastic models in analytics

In analytics, stochastic models play the role of introducing uncertainty and unpredictability into the decision-making process. These models assess and quantify uncertainty in various areas of the decision-making process using statistical methods and concepts from probability theory. Stochastic models enable prescriptive analytics to deliver more reliable and precise decision-making solutions by considering the unpredictability and associated dangers. Optimization methods and stochastic models are used in prescriptive analytics to recommend the optimum course of action while taking limitations and potential uncertainties into account. Organizations may make better decisions that not only optimise outcomes but also take into consideration potential risks and uncertainties by integrating stochastic models into prescriptive analytics. Organizations can take into account both the ideal solution and any risks and uncertainties when making decisions thanks to prescriptive analytics' use of stochastic modelling and optimization methodologies(Yange et al., 2020).

Utilizing both efficiency and optimization as well as the uncertainties found in real-world circumstances, this combination enables firms to make better informed and reliable judgments. To deal with the uncertainties that come with decision-making, prescriptive analytics and stochastic modelling are combined. This strategy is especially useful when there is unpredictability related to the weather, equipment problems, changes in market demand, and other sources of uncertainty. Organizations can better comprehend the consequences and risks associated with various decision options by introducing stochastic models into prescriptive analytics.

2.7.3 Incorporating stochastic models

Probability theory and statistical techniques are used to predict and quantify uncertainties when stochastic models are incorporated into prescriptive analytics. These ambiguities may be caused by a variety of factors, including changes in consumer demand, problems with the supply chain, or malfunctions with the machinery. The unpredictability and possible dangers associated with these uncertainties can be captured and analysed by organisations using stochastic models. Stochastic models allow prescriptive analytics to deliver more reliable and precise decision-making solutions by taking into account the distribution of potential outcomes and their probability. For instance, stochastic simulation and statistical learning approaches can be utilised in predictive analytics to forecast market demand and optimise production schedules in the manufacturing sector.

Prescriptive analytics, on the other hand, is useful for making choices based on these forecasts. Predicting future events is only one aspect of prescriptive analytics. Additionally, it considers the restrictions, goals, and trade-offs that go into making decisions. To accomplish desired results while considering a variety of limitations and uncertainties, prescriptive analytics employs optimization techniques to determine the best potential decisions and actions. For instance, in the manufacturing sector, prescriptive analytics can aid in the optimization of production processes by finding the best distribution of resources, such as machinery, manpower, and raw materials, considering limits on cost, time, and quality. Organizations can learn more about the potential risks and uncertainties linked to various decision-making options by using prescriptive analytics and stochastic models. Organizations can assess the robustness and dependability of their judgments under uncertainty by introducing stochastic models into prescriptive analytics. Organizations have the ability to assess the risks and probable outcomes of various decision-making options thanks to prescriptive analytics and stochastic models.

2.7.4 Bridging the gap from descriptive to prescriptive analytics

With its emphasis on optimization and stochastic models, prescriptive analytics fills the gap between descriptive analytics, which only summarise past occurrences, and predictive analytics, which predicts future events. The following step is taken by prescriptive analytics, which suggests the optimal course of action to accomplish the intended results(Yange et al., 2020).

Combining stochastic models with prescriptive analytics and optimization approaches enables firms to make data-driven decisions that maximise goals while taking uncertainties and restrictions into account. Compared to conventional point estimate-based optimization techniques, these cutting-edge methodologies provide a more reliable approach to decision-making.

They consider the possible risks and uncertainties linked to various decision possibilities, enabling companies to assess the robustness and reliability of their choices. In decision-making scenarios where the best course of action depends on ambiguous parameters or variables, prescriptive analytics with stochastic models is particularly helpful. Organizations can assess the probable consequences and risks associated with various decision-making options by integrating stochastic models into prescriptive analytics. The most effective routes and schedules for waste collection trucks, considering factors like traffic conditions, collection demand, and vehicle capacity constraints, can be determined, for example, in waste collection systems using prescriptive analytics with mathematical programming and simulation models(Vargas et al., 2022). Prescriptive analytics can make suggestions that are more precise and trustworthy by utilising stochastic models. Additionally, prescriptive analytics and optimization methods using stochastic models help firms manage uncertainty and unpredictability in decision-making.

2.8 CONCLUSION

Simulation models have the potential to minimize patient waiting time by offering healthcare providers solutions to evaluate various situations and determine the optimal allocation of resources and staff. Simulation models are a valuable tool for the identification of bottlenecks within the patient flow process. These models facilitate the recognition of issues such as extended waiting periods for specific operations or inadequate staffing levels in particular locations. Through the identification of these bottlenecks, healthcare practitioners can implement system modifications aimed at mitigating waiting times.

The utilisation of simulation models enables the examination of various scenarios, encompassing the manipulation of staff numbers and the modification of appointment schedules. Through the process of experimentation with various scenarios, healthcare professionals can ascertain the optimal approach for allocating resources and personnel to effectively mitigate waiting times. Simulation models have the potential to enhance patient flow within healthcare settings by facilitating the optimisation of resources and personnel utilization. One potential approach to enhancing patient flow and minimizing waiting times in healthcare settings involves modifying staffing levels in specific regions or reordering procedural sequences.

Simulation models can serve as a decision-making tool for healthcare providers in determining strategies to mitigate patient waiting times. Healthcare providers can enhance their decision-making about patient flow optimization and waiting time reduction by employing visual representations of the system and conducting various scenario tests. In general, simulation models possess significant utility for healthcare practitioners in their efforts to mitigate patient waiting time..

CHAPTER III

RESEARCH METHODOLOGY

3.1 INTRODUCTION

The methods used to ensure that the acquired data are organised and analysed to provide helpful insights and isolate the potential causes of an increase in waiting time make up the research methodology approach to the study.

Simulation methodology works best for further bolstering the suggested solutions and supporting the chosen course of action. Given that the prediction of patient arrival time and treatment time are two example variables with random possibilities, the Monte-Carlo method is chosen as the appropriate model to simulate a proposed method because the random values used in this scenario will produce a situation that is similar to that found in real world settings.

Simulation is thought of as a top implementation strategy in research and decision-making. It is used as an effective technique to develop new methods for creating and improving clinical workflows and simulation of cost analysis to help industry experts create solutions for current business needs.

3.2 THE EXPERIMENTAL DESIGN

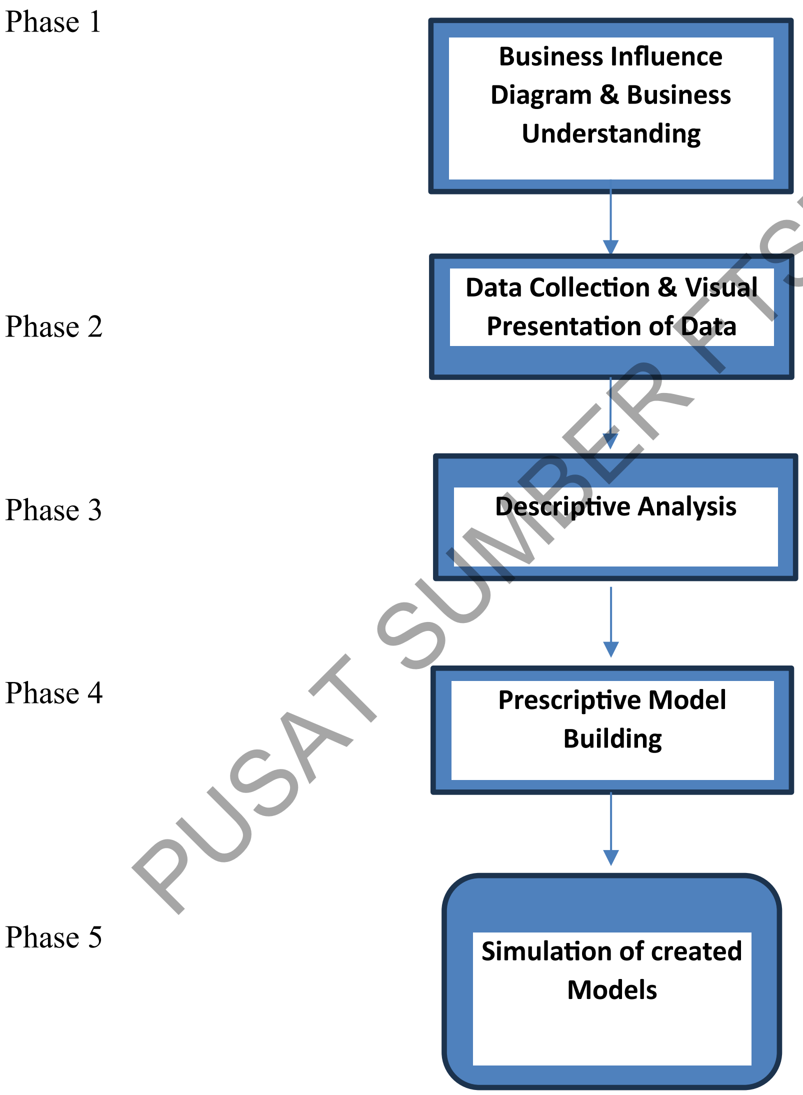

Figure 1.0 Phases Of The Research Framework

The research framework used in this study will be presented in this part. The research's framework will be utilized to organize the steps that were taken. It is frequently used as a guide by researchers to assist them in focusing their research. The study is divided into five stages.

Phase 1 should begin with a thorough understanding of the system and the definition of its key performance metrics as well as the decision variables that have a major impact on those indicators. The collecting of data and the identification of performance measures mark the end of phase one.

Phase 2 will study the data obtained and transform the data into understandable charts that will reveal and isolate the metrics that will be chosen to optimize patient waiting time.

Phase 3 A descriptive analysis models will be used to find a relationship between the attributes and if possible to form a conclusion or reinforce a theory.

Phase 4, a model and representation of the variables including patient arrivals, service times, waiting times, and process-flow data are described. The flow of patients are established and the way things were done in order to comprehend the system. a mathematical model using the determined objective functions.

Phase 5 involves creating a simulation model using data gathered from the observations. A t-test is used to validate the simulation model. The mathematical models are then leveraged using Microsoft Excel and incorporated into the proposed simulation model.

3.3 BUSINESS GOAL STATEMENT

A proper understanding of the organisations business goals is the first step to deciding the correct data to be used in analysis. It is also necessary to understand the organisations previous business decisions to better decide on creating a model. In this study, the main business goal is to reduce waiting time and increase patient turnover

3.3.1 Business influence diagram

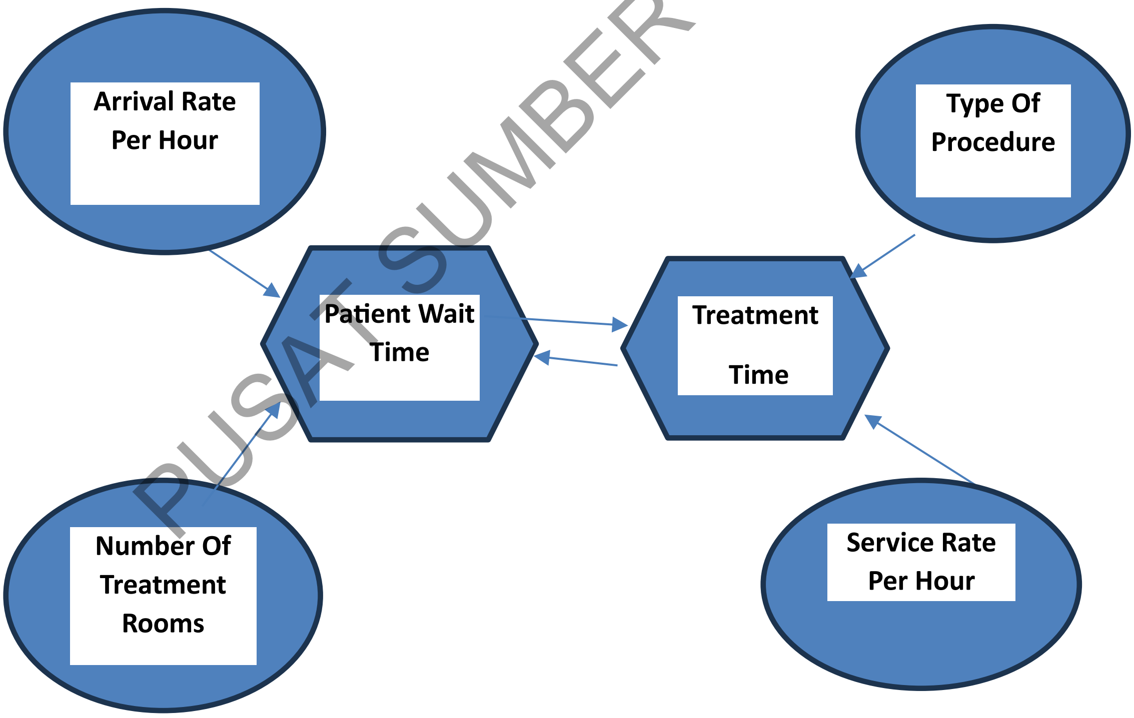

Figure 1.1 Business Influence Diagram

The business influence diagram *(shown in Figure 1.1*) is determined with collecting Key Performance Indictors, observation, conducting interviews with staff and stakeholders. Patient Data was collected according to the needed key performance metrics.

3.4 SETTING & DATA SOURCE

The case site for the current study is a hospital. The hospital's active medical team oversees 1000 licensed beds. Each year, it serves more than 600,000 patients. The hospital's The department provided data for the current study. Management tools, such as the time stamps for each patient visit and the inpatient records, were crucial. Relevant time stamps included the patient's arrival at the hospital, their arrival in the treatment room, and the time of their procedure.

The acquired raw data comprised of two distinct files which are patient demographics and queue system data. The queue system data included information such as the time when a ticket was issued, the type of service provided, the designated service room, and the time at which the patient entered the investigation room. A total of 1762 data entries were presented.

Cleaning and repairing erroneous data structures were part of the data cleaning and validation process. Less than 5% of the total data obtained contained errors. The following two tables *(shown in table 1.0 -1.3)* is the sample of the raw data obtained and its missing data.

Date	Service	Service Room	App Tim	TicketN	TicketIssuedTim	ServedTim	ServeTimeMinute
1/30/1995	echocardiography Type B	A	08:15:00	2231	08:09:20	08:19:11	00:38:43
1/30/1995	echocardiography Type C	A	10:30:00	2254	08:11:07	08:57:54	00:03:38
1/30/1995	echocardiography Type A	A		2274	08:42:55	09:01:32	00:43:38
1/30/1995	echocardiography Type A	A		2275	09:05:03	09:45:10	00:49:01
1/30/1995	echocardiography Type A	A		2277	09:55:05	10:34:11	00:47:36
1/30/1995	echocardiography Type C	A	09:45:00	2253	10:48:20	11:21:47	00:41:06

Figure 1.2 Sample Of The Obtained Raw Data

Date	Service	Service Room	App Tim	TicketN	TicketIssuedTim	ServedTim	ServeTimeMinute
1/28/1995	#N/A	N		2141	07:48:11	08:08:57	00:37:00
1/25/1995	#N/A	H		2144	10:14:43	11:19:08	01:11:32
1/25/1995	#N/A	I		2143	09:27:56	09:34:14	00:29:25
1/22/1995	#N/A	N		2141	08:10:33	08:22:40	00:32:19
1/21/1995	#N/A	N		2142	10:44:19	12:10:38	#VALUE!
1/18/1995	#N/A	N		2142	08:11:42	08:35:33	00:31:20
1/18/1995	#N/A	N		2143	08:45:20	09:06:53	00:31:56

Figure 1.3 Sample Of The Missing Data Obtained

Date	Service	Service Room	App Tim	TicketN	TicketIssuedTim	ServedTim	ServeTimeMinute
1/1/1995		#N/A	10:00:00	2313	09:41:19		10:14:31

Figure 1.4 Sample of the missing data obtained

Missing data obtained was recovered by mapping out the service room to the service provided, based on the complete data. In one example *(shown in table 1.2)* where insufficient details are provided, were omitted.

Date	Service	Service Room	ServedTime	Waiting Time	Service rate	AvgWaitTimebyRoomMinutes	MaxWaitTimebyRoomMinutes	MinWaitTimebyRoomMinutes
1/1/1995	echocardiography Type C	F	8:12:42 AM	25	9	47	138	4
1/1/1995	echocardiography Type D	E	8:12:53 AM	27	9	39	130	4
1/1/1995	echocardiography Type A	C	8:33:33 AM	19	9	50	142	3
1/1/1995	echocardiography Type C	A	8:37:59 AM	16	9	35	115	4
1/1/1995	echocardiography Type C	C	8:46:37 AM	36	9	50	142	3
1/1/1995	echocardiography Type B	M	8:50:23 AM	34	9	47	179	9
1/1/1995	echocardiography Type D	D	8:54:48 AM	33	9	48	188	3

Figure 1.5 Sample Of The Amended Dataset

To understand the patient flow, new attributes were added to the dataset namely service rate, waiting time, average waiting time *(shown in table 1.3)* according to room was created. Service rate was calculated based on the number of served time in a service per hour. The amended dataset has 1731 data entries.

3.5 DATA VISUALIZATION

Data obtained comprises of patient demographics, Identity Number, given appointment time, time of arrival, time waiting, procedure time. The information received excludes specific information related to the procedure, such as staff interaction with patients and downtime. Using Microsoft Excel, the data was cleaned to reduce mistakes from the collected data. The cleaned dataset was analysed in Microsoft Excel and Python using Jupyter Notebook. In this dataset, the presented topics are shown to create insights on how the model will be created.

3.6 PATIENT ARRIVAL RATE

Patient arrival rate according to hour in the dataset was calculated according to the count of tickets issued per hour. The average arrival of patients are plotted in the graph below

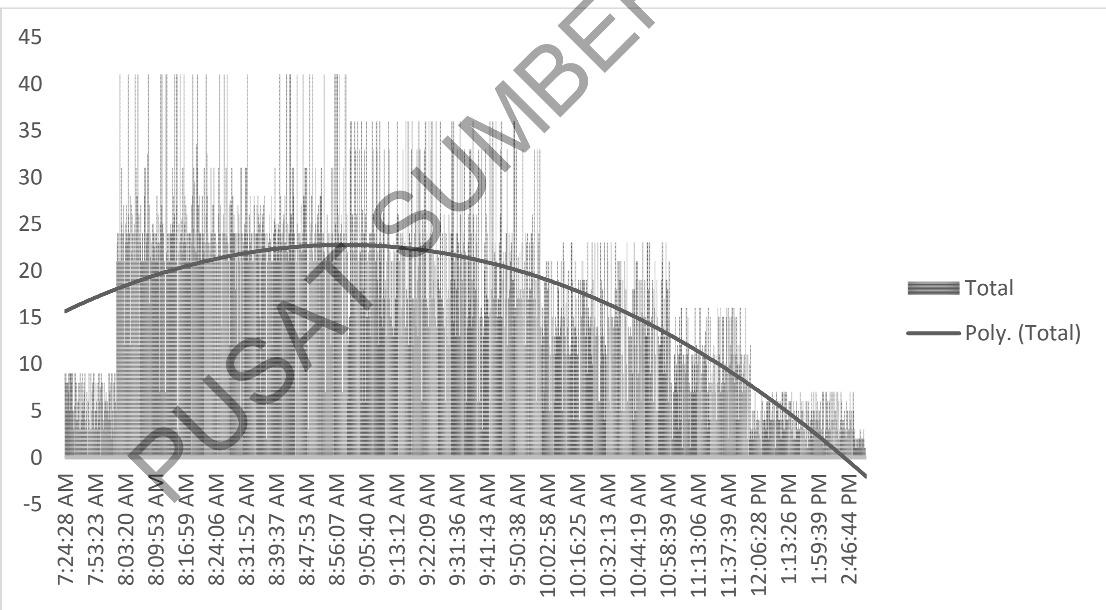

Figure 1.6 Average Arrival Rate According To Hour

The above chart *(figure 1.2)* shows the distribution of arrival according to time. Patients prefer to come to the department at 8.00AM -10.00AM.

3.6.1 Distribution of queue

Waiting time for procedure was classified according to average waiting time according to hour. Dataset display as follows *in Table 1.5.*

Table 1.0 table of average arrival time according to hour

8 AM	9 AM	10 AM	11 AM	12 PM	1 PM	2 PM	3 PM	4 PM
40.23	**40.26**	**36.26**	**29.70**	**41.07**	**41.39**	**30.01**	**24.59**	**4.36**

Minutes

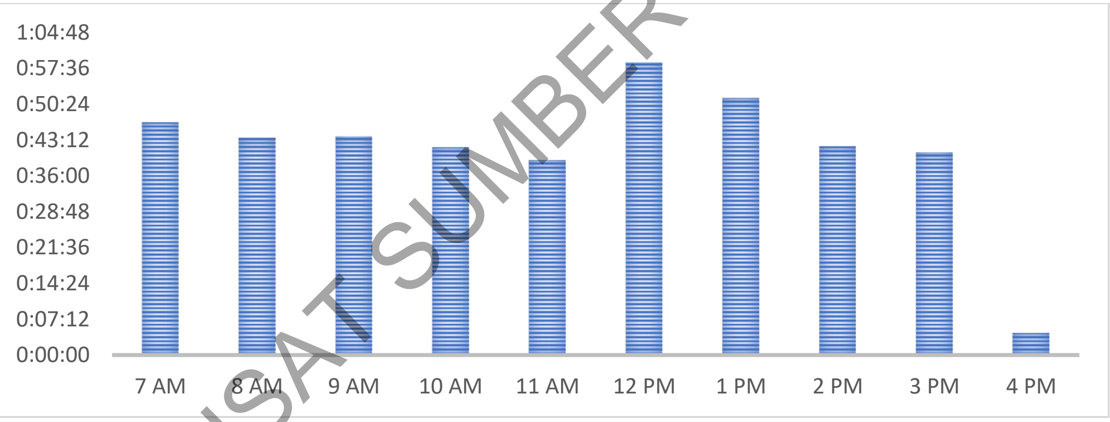

Figure 1.7 Average Clinic Waiting Time By Hour

Bar chart above *(Figure 1.3)* shows the waiting time classified by hour. The waiting time shows a reducing trend over the hours. An early inference can be made to assume that the waiting time is heavily influenced by the arrival rate.

3.7 PROCEDURES

The procedures carried out in the department was analysed and a plot graph was created to understand the patient distribution by service and patient distribution by service room.

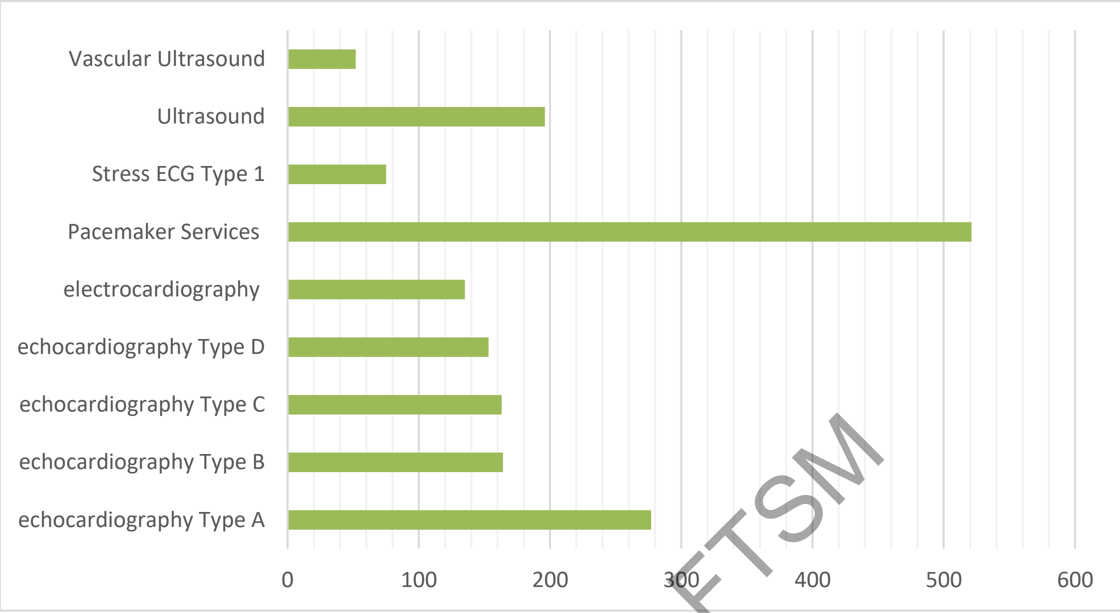

Figure 1.8 Total Distribution Of Patients According To Service Type For One Month

In the chart above *(Figure 1.4)* most patients appointments are echocardiography a total of 757, followed by pacemaker service with a total of 521, followed by ultrasound with a total of 248, the least distribution of patients are to electrocardiography and stress electrocardiography with a total of 210 patients.

Distribution of patients according to service room is also obtained to determine the patient load queuing to one room, since each room will create a queue, it is important that the daily queue to the room is not too long as it would create a backlog of appointments.

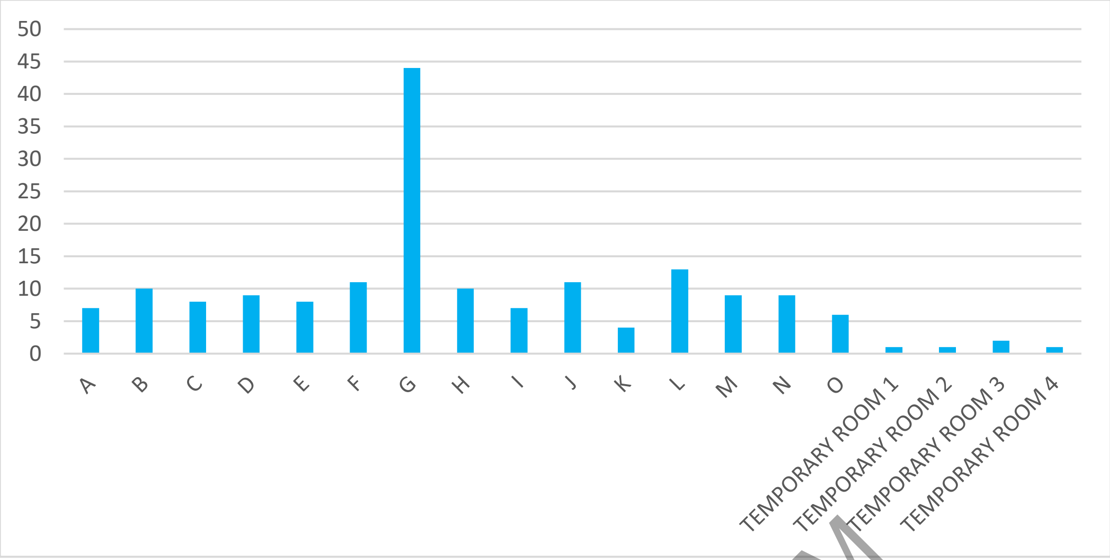

Figure 1.9 Patient Distribution According To Room

The above *(refer figure 1.5)* bar chart shows the distribution of patients according to room. The dots represent the maximum number of patients queuing to a room in a day. Most rooms are serving an average of 8 patients a day apart from the pacemaker room G is serving an average 22 patients a day.

3.8 TOTAL WAIT TIME

Total wait time is measured from the time of patient arrival till their procedure is complete. Wait times is calculated and classified into average service wait times and wait time according to room.

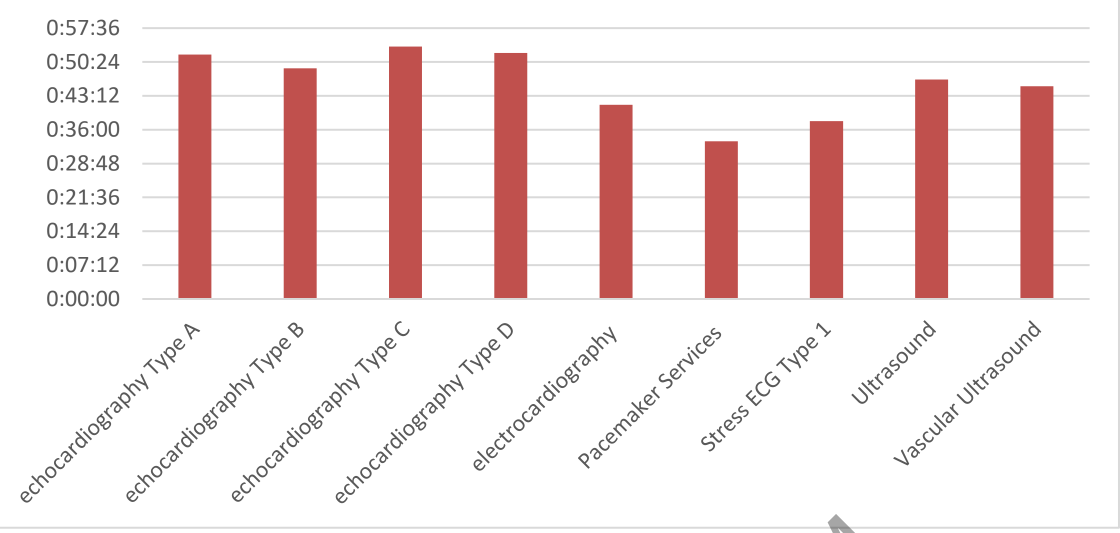

Figure 2.0 Average Total Wait Time According To Service

The average total wait time according to service *(figure 1.6)* shows a range of 33 minutes to 51 minutes.

Echocardiography takes 50 minutes on average. Electrocardiography takes an average of 40 minutes. Pacemaker services takes 33 minutes, and ultrasound takes 45 minutes on average.

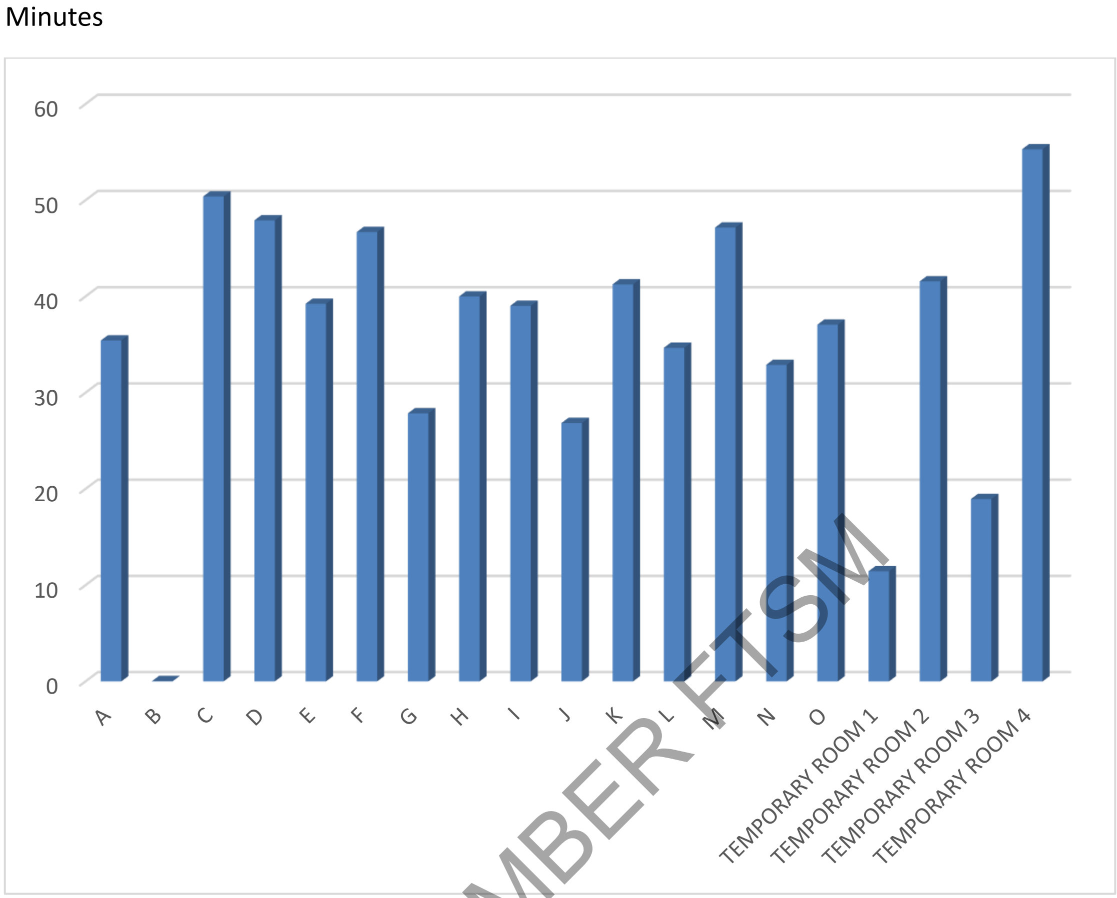

Figure 2.1 Average Wait Time According To Room

The average wait time for each room shown in *(figure 1.7)* shows there is a slight difference between rooms. Room A-F,K & M is for echocardiography, Room L does electrocardiography. Pacemaker is carried out in rooms G, F, J, L. ultrasound is carried out in room H & I. Vascular ultrasound is room O. Stress electrocardiography is done in room N.

3.9 CONCLUSION

The acquired raw data comprised of two distinct files which are patient demographics and queue system data. The queue system data included information such as the time when a ticket was issued, the type of service provided, the designated service room, and the time at which the patient entered the investigation room.

Additional attributes were incorporated into the dataset, encompassing waiting time, service time, arrival rate, and the total number of patients queuing for a room during a given day. Missing data has been corrected by mapping the room to the service and in one example where both room and service was not provided, was randomized into a service room and corresponding procedure.

The data visualization presented in *Figure 1.2* and *Table 1.5* illustrates the distribution of arrival rates throughout the day. It reveals that the number of patients arriving in the morning is greater than the number arriving in the afternoon. The cumulative patient queue in the depicted room (*refer to Figure 1.5*) is not deemed substantial within this context, as it is expected that other hospitals will have a minimum of three times the number of patients.

The data indicates that there is a higher concentration of pacemaker service distribution, particularly in room G, as depicted in *Figure 1.5*. This observation suggests the presence of an outlier within the dataset, although it does not appear to have any impact on the service rate.

The dataset contains an ample amount of data that may be utilized in diverse analytical models. However, it is important to note that no substantial machine learning model has been developed to establish a correlation between the variables. Consequently, descriptive analysis report has been excluded from the dissertation.

CHAPTER IV

MODELING

4.1 INTRODUCTION

The main objective of this project is to provide a decision support tool that the hospital management may utilise to suggest improvements to their present workflow. Chapter begins with an attempt to identify the best model to interpret the data. The major goal is to shorten wait times at the outpatient clinic while also raising overall satisfaction levels for both patients and medical staff.

The chapter includes the suggested mathematical model, which considers the competing constraints and the multi-objective needed to optimize patient scheduling process. Python will be used to use to generate the created model. The model's outcomes are covered in Chapter 5.

4.2 OPERATIONAL RESEARCH BASED QUEUE MODEL

This section focuses on creating a functional model in the design of a queue-based Monte Carlo simulation is the main topic of this section. The model extends the approach and incorporates concepts from queuing theory.

4.2.1 MODEL DESIGN

To determine the typical arrival rates based on the day of the week and hour of the day before creating the model, descriptive statistics were run on the patient records. The information was entered into Excel, and distributions of the standard wait and service times were also computed. To reflect changes more accurately in the hospital's department, the model incorporates aspects from discrete event simulation and queuing theory. Excel was used to create the model because of its basic structured query tools, native support for mathematical functions, and simplicity of vector and matrix operations. However, because the queuing model is a special simulation, it is allowed that the program may be utilized when developing similar models

4.2.2 Data descriptive statistics

Descriptive visualizations of the dataset are shown in the following tables, where service rate of each procedure will be examined and be used in calculating queueing optimization and later, used in developing the Monte-Carlo model.

Electrocardiography

	Date	ArrivaltoServeMinutes	PatientServedHourbyService	AvgWaitTimebyRoomMinutes	MaxWaitTimebyRoomMinutes	MinWaitTimebyRoomMinutes
count	135	135.000000	135.000000	135.000000	135.000000	135.000000
mean	1995-01-18 14:56:00	33.566667	2.007407	34.752593	167.687556	7.111704
min	1995-01-01 00:00:00	9.016667	1.000000	34.660000	167.600000	7.100000
25%	1995-01-13 00:00:00	20.150000	1.000000	34.660000	167.600000	7.100000
50%	1995-01-20 00:00:00	28.616667	2.000000	34.660000	167.600000	7.100000
75%	1995-01-27 00:00:00	38.675000	2.000000	34.660000	167.600000	7.100000
max	1995-01-30 00:00:00	126.650000	4.000000	47.160000	179.420000	8.680000
std	NaN	21.392731	0.918275	1.075829	1.017304	0.135985

Figure 2.2 Descriptive Statistics Of Electrocardiography Procedure

Echocardiography

	Date	ArrivaltoServeMinutes	PatientServedHourbyService	AvgWaitTimebyRoomMinutes	MaxWaitTimebyRoomMinutes	MinWaitTimebyRoomMinutes
count	754	754.000000	754.000000	754.000000	754.000000	754.000000
mean	1995-01-16 07:26:53.793103488	45.212202	6.053050	42.954907	131.737401	4.612732
min	1995-01-01 00:00:00	2.000000	1.000000	35.000000	48.000000	2.000000
25%	1995-01-08 00:00:00	22.000000	4.000000	35.000000	115.000000	3.000000
50%	1995-01-17 00:00:00	39.000000	6.000000	47.000000	138.000000	4.000000
75%	1995-01-23 00:00:00	62.000000	8.000000	48.000000	179.000000	4.000000
max	1995-01-30 00:00:00	188.000000	12.000000	50.000000	193.000000	29.000000
std	NaN	30.647246	2.646975	5.907708	45.314982	2.781775

Figure 2.3 Descriptive Statistics Of Echocardiogeraphy Procedure

Pacemaker

	Date	ArrivaltoServeMinutes	PatientServedHourbyService	AvgWaitTimebyRoomMinutes	MaxWaitTimebyRoomMinutes	MinWaitTimebyRoomMinutes
count	519	519.000000	519.000000	519.000000	519.000000	519.000000
mean	1995-01-14 22:39:32.254335232	28.924342	7.186898	29.170501	157.462062	4.147399
min	1995-01-01 00:00:00	2.083333	1.000000	26.850000	47.730000	2.350000
25%	1995-01-06 00:00:00	11.983333	4.000000	27.860000	158.000000	3.800000
50%	1995-01-14 00:00:00	21.433333	7.000000	27.860000	158.000000	3.800000
75%	1995-01-23 00:00:00	37.083333	10.000000	27.860000	158.000000	3.800000
max	1995-01-30 00:00:00	167.600000	24.000000	46.700000	167.600000	7.100000
std	NaN	24.810662	4.007924	3.797224	8.484545	1.020632

Figure 2.4 Descriptive Statistics Of Pacemaker Procedure

Stress Electrocardiography

	Date	ArrivaltoServeMinutes	PatientServedHourbyService	AvgWaitTimebyRoomMinutes	MaxWaitTimebyRoomMinutes	MinWaitTimebyRoomMinutes
count	75	75.000000	75.000000	75.0	75.0	75.0
mean	1995-01-14 09:16:48	32.893333	1.426667	33.0	119.0	6.0
min	1995-01-01 00:00:00	3.000000	1.000000	33.0	119.0	6.0
25%	1995-01-06 00:00:00	13.000000	1.000000	33.0	119.0	6.0
50%	1995-01-17 00:00:00	23.000000	1.000000	33.0	119.0	6.0
75%	1995-01-21 00:00:00	47.500000	2.000000	33.0	119.0	6.0
max	1995-01-29 00:00:00	119.000000	2.000000	33.0	119.0	6.0
std	NaN	26.062074	0.497924	0.0	0.0	0.0

Figure 2.5 Descriptive Statistics Of Stress Electrocardiography Procedure

Ultrasound

	Date	ArrivaltoServeMinutes	PatientServedHourbyService	AvgWaitTimebyRoomMinutes	MaxWaitTimebyRoomMinutes	MinWaitTimebyRoomMinutes
count	196	196.000000	196.000000	196.000000	196.000000	196.000000
mean	1995-01-16 02:48:58.775510144	40.110629	2.459184	39.453061	178.839643	3.223469
min	1995-01-01 00:00:00	3.633333	1.000000	35.430000	115.130000	2.000000
25%	1995-01-08 00:00:00	17.712500	2.000000	39.030000	169.170000	2.000000
50%	1995-01-15 00:00:00	32.166667	2.000000	39.030000	169.170000	4.170000
75%	1995-01-24 00:00:00	52.995833	3.000000	40.000000	193.100000	4.170000
max	1995-01-30 00:00:00	193.100000	6.000000	46.700000	193.100000	4.170000
std	NaN	30.996247	1.208248	0.815382	13.799440	1.074457

Figure 2.6 Descriptive Statistics Of Ultrasound Procedure

Vascular Ultrasound

	Date	ArrivaltoServeMinutes	PatientServedHourbyService	AvgWaitTimebyRoomMinutes	MaxWaitTimebyRoomMinutes	MinWaitTimebyRoomMinutes
count	52	52.000000	52.000000	52.000000	52.000000	52.000000
mean	1995-01-16 05:04:36.923076864	39.631410	1.346154	36.873462	109.999615	2.390962
min	1995-01-01 00:00:00	2.050000	1.000000	26.850000	109.130000	2.350000
25%	1995-01-08 00:00:00	17.258333	1.000000	37.070000	109.130000	2.350000
50%	1995-01-15 00:00:00	29.591667	1.000000	37.070000	109.130000	2.350000
75%	1995-01-24 00:00:00	61.545833	2.000000	37.070000	109.130000	2.350000
max	1995-01-29 00:00:00	109.133333	2.000000	37.070000	154.350000	4.480000
std	NaN	28.645549	0.480384	1.417259	6.270886	0.295378

Figure 2.7 Descriptive Statistics Of Vascular Ultrasound Procedure

In the descriptive tables shown, service rate is labelled as patient served hour by service. The mean service rate will be used in the following sections of this chapter and will be referred as Miu or μ.

4.3 BASIC QUEUEING FORMULAS

Little's rule provides the following results:

1. $L = \lambda W$

2. $Lq = \lambda Wq$

The first of the statements is true of both the system and the queue, which is a component of the system. One more beneficial connection in the queue is:

3. $W = Wq + 1/\mu$

it states that the mean wait in the system is equal to the product of the mean wait in the queue and the service time (1/ **μ**).

4.3.1 Queueing notation

To represent queues, use the notation shown below: A/B/c/K, where K represents the queue's capacity and A represents the distribution of inter-arrival time, B the distribution of service time, and c the number of servers. We presume that K is if K is absent.M, which is short for Markov, is frequently used to represent the exponential distribution. A queue that has one server (and one channel) and exponentially distributed inter-arrival and service times is known as an M/M/1 queue. An M/G/1 queue is a queue with one server in which the service time is generally distributed, that is, the service time has any given distribution, and the inter-arrival time is exponentially dispersed.

λ: mean rate of arrival and equals 1/E[Inter-arrival-Time], where E denotes the expectation operator.