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Improving Radiology Workflow Efficiency: Insights from Simulation-Based Operational Modeling

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Abstract

Healthcare systems are challenged globally to provide high-quality care while managing limited resources and budgets. Radiology departments provide critical diagnostic services to nearly every medical discipline. Delays in imaging services can unnecessarily extend patient hospital stays and lead to overcrowding in inpatient departments. Therefore, any inefficiencies in radiology can have cascading effects on the operations of other departments and the hospital's performance as a whole. Despite the importance of improving workflow efficiency in radiology departments, little attention has been paid to detailed case studies that investigate its specific challenges. This study addresses this gap by applying a simulation-based analysis to a radiology department in a major hospital in Saudi Arabia. A validated discrete event simulation model was developed through a comprehensive analysis of historical records and close collaboration with stakeholders. The findings highlight the transformative potential of simulation in providing actionable insights for healthcare managers and enhancing department performance. The results of Scenario 2 (Demand-Based Scheduling) outperformed those of Scenario 1 (Adjusted Staffing), achieving a 60% improvement in resource utilization and 40% cost savings relative to the baseline model. However, implementing demand-based scheduling introduces greater scheduling complexity and may lead to increased staff resistance. A phased transition strategy is suggested to maximize long-term benefits while minimizing disruptions to operations. Future research should focus on empirical validation through assessing the implementation in a real-world hospital setting to strengthen the applicability of the findings.

Keywords
Healthcare, simulation, modelling, workflow.

1. Introduction
Healthcare systems are challenged globally to provide high-quality care while managing limited resources and budgets. The complexity of healthcare delivery derived from growing populations, restricted recruitment pools, and technological advancements has amplified the need for optimizing operations. In order to utilize resources efficiently, hospitals need to streamline workflows to sustain serving growing patient volumes while maintaining accessibility of healthcare services. Radiology departments provide critical diagnostic services that enable treatment planning. Nearly every department in the hospital relies on accurate and timely imaging services to guide patient care. Delays in imaging services can unnecessarily extend patient hospital stays and lead to overcrowding in inpatient departments. Therefore, any inefficiencies in radiology can have a cascading effect on the operations of other departments and the hospital's performance as a whole.

To sustain high levels of efficiency, radiology departments must balance resource allocations with patient arrival volumes. However, prolonged patient waiting times, high or low levels of resource utilization and workforce scheduling issues can arise due to an inflexible staffing structure and shifts that fail to accommodate the dynamic nature of patient demand.

Despite the importance of improving workflow efficiency in radiology departments, little attention has been paid to detailed case studies that investigate its specific challenges. This study addresses this gap by applying a simulation-based analysis to a radiology department in a large Saudi hospital. The assessment of the current operations in the department through simulation enables the development and evaluation of interventions aimed at improving overall efficiency, minimizing costs, and improving patient throughput. The remainder of the paper has been divided into four sections. Section 2 reviews the relevant literature on simulation studies in healthcare. Section 3 describes the research methodology and the model development process. Section 4 presents the findings and discusses the proposed scenarios. Finally, Section 5 concludes the study and outlines areas for future research.

2. Literature Review

The academic literature has revealed the emergence of simulation as a transformative improvement tool in healthcare. In this section, we synthesize insights from relevant publications, highlighting the use of simulation in healthcare, advanced simulation techniques, its applications in radiology and the context of the Saudi healthcare system.

2.1 Simulation in Healthcare

Simulation techniques are recognized for their ability to model stochastic and dynamic systems. Discrete Event Simulation (DES) in particular, have been widely used to analyze healthcare systems and evaluate potential improvement initiatives due to its ability to model the variability present in healthcare operations. Complexity and variability in healthcare operations can increase significantly in pandemics (Alrabghi and Tameem 2025). Classic examples of simulation in healthcare include modelling patient flow, staff scheduling and medical resources allocation (Forbus and Berleant 2022). Recent reviews of simulation in healthcare reveal applications in divers areas such as emergency care, intensive care units and outpatient clinics (Vázquez-Serrano et al. 2021). These models assist in identifying and analyzing bottlenecks, evaluating scenarios and supporting decision making without a negative impact on the real system (Kalwar et al. 2021).

Radiology is central to the healthcare operations as physicians from various specialties refer their patients for diagnosis. Therefore, streamlining the operations in the radiology department by minimizing waiting times and maximizing patient throughput can have a wider effect on the performance of other departments in the hospital. Nonetheless, few empirical studies have investigated the exclusive application of simulation on radiology. This gap highlights the need for further research to address the unique challenges in radiology such as high demand variability and coordination with other departments (Pierre et al. 2023).

2.2 Advances in Simulation Techniques

A number of studies have begun to examine the integration of data-driven approaches in simulation modeling. Process mining techniques are leveraged to transform the high volume of event logs in the hospital information system into actionable insights. A case study involving the application of data driven process simulation on a radiology department in a Belgium hospital demonstrated its role in decision making including determining the required number of radiology devices, reception staff scheduling and the size of the waiting area. (Hulzen et al. 2022).Simulation can be coupled with optimization to enable faster and more efficient search for optimal solutions especially in cases where the decision problem is mathematically intractable and the solution space is vast and complex. Examples of simulation optimization in healthcare includes applications in resource planning both in emergency departments and inpatient care. The integration of optimization with simulation has been shown to be effective in addressing capacity constraints and enhancing the delivery of healthcare services. (Wang and Demeulemeester 2023).

Hybrid modelling techniques combining simulation, forecasting and optimization are becoming more popular. A novel framework is proposed to optimize the level of resource across an entire hospital in the UK. The main components of the framework include a Discrete Event Simulation model, a forecasting process to predict hospital demand and a linear programming optimization module. Such frameworks enable conducting comprehensive analysis and gaining insights across the hospital as well as supporting operational decisions. (Ordu et al. 2021).

Industry 4.0 technologies such as big data analytics, cloud computing and IoT are transforming operational performance in healthcare. These technologies can provide valuable input to predictive modeling and simulation, enhancing the model's accuracy and enabling scalability. This might pave the way for developing digital twins that optimize patient waiting times and the allocation of healthcare professionals in real time. (Ilangakoon et al. 2022).

Artificial intelligence (AI) has the potential to complement simulation by analyzing the patient workflow and learning from experience. Machine learning and natural language processing tools can be integrated with simulation to prioritize worklists and predict waiting times, appointment delays and diagnosis duration based on environment and patient specific factors. This allows for producing more efficient schedules, which in turn improve the workflow and enhances both patient and staff satisfaction. (Pierre et al. 2023).

2.4 Simulation in the Saudi Healthcare Context

The healthcare system in Saudi Arabia is undergoing significant reforms, emphasizing efficiency and privatization. Studies show that most Saudi healthcare professionals and managers believe that simulation can be a key enabler in achieving these goals. However, only few application cases have been reported in literature. Barriers to simulation implementation include awareness of simulation as an improvement tool, lack of simulation professionals and lack of sufficient time to develop simulation models (Alrabghi 2020). Nonetheless, the few studies of simulation in Saudi healthcare demonstrate significant results including reduction in patient waiting time and enhanced resource efficiency (Alrabghi and Tameem 2024).

3. Methods

The present study utilizes Discrete Event Simulation (DES) to analyze and improve the workflow of the radiology department in a large hospital. DES is a modelling technique that tracks changes affecting a given system at discrete points in time such as patients arrivals and the start of a diagnosis procedure. It has been used extensively to model complex and stochastic systems. Imitating the operations of the department allows for the assessment of the current configuration as well as the evaluation of proposed scenarios and interventions without negatively impacting the actual operations. (Law 2024).

As shown in Figure 1, the simulation modelling follows a systematic process involving four key steps: (i) conceptual design, (ii) input analysis, (iii) model development, verification and validation, and (iv) output analysis and experimentation. The process is agile and iterative requiring regular adjustments in previous steps as needed. (Smith and Sturrock 2024).

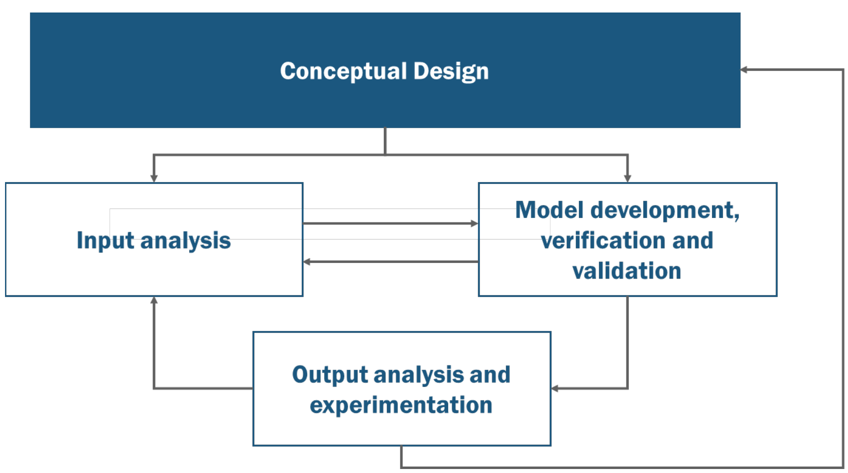

Figure 1. - Main steps in the simulation process. Source (Smith and Sturrock 2024)

3.1 Conceptual Design

The first step in the simulation process involves outlining the main components of the system in interest including the workflow and the dependency among various components. It requires a detailed understanding of the system. In this study, the conceptual design of key processes such as patient arrivals, registration, imaging and departure was developed based on field visits, observations and discussions with stakeholders. This is to ensure that the model will reflect the actual workflow and priorities of the department.

3.2 Input Analysis

This step includes collecting and analyzing input data such as patient interarrival patterns, registration times, schedules of sonographers, types of diagnosis procedures and the duration for each procedure. Sources of data included access to the hospital's database, observations and expert input. Statistical analysis and distribution fitting were employed to enable the characterization and modelling of stochastic processes. This includes visualizing the data and assessing the descriptive statistics, nominating a number of candidate statistical distributions, conducting goodness-of-fit tests and eyeball visual tests. The most suitable statistical distribution is selected to be used as an input to the simulation model.

3.3 Model Development, Verification, and Validation

The object-oriented simulation software (Simio) was utilized to translate the conceptual design into a computer simulation model. Advantages of such software includes rapid modelling and auto-generated statistics. The model was verified by introducing visual animations and dashboards to ensure it is free from logical errors. The results of the model were compared to metrics in historical database to confirm its validity. Iterative adjustments were made continuously whenever inconsistency was identified.

3.4 Output Analysis and Experimentation

A number of scenarios were run to evaluate the proposed interventions such as changes in resource levels and shifts patterns. The effect was assessed on key metrics such as the utilization of sonographers and patient waiting times. The stochastic output required conducting a number of replications for each scenario as well as analyzing and interpreting the output statistically using box plots and confidence levels and intervals.

Following the iterative process ensures that the model accurately represents real-world dynamics and aligns with stakeholder needs. Therefore, the study outlines actionable insights and practical recommendations suitable to the current challenges faced by the radiology department.

4. System Description

As depicted in Figure 2, the patient journey within the radiology department starts with the reception desk where the diagnosis order is retrieved from the Radiological Information System and the patient's arrival is registered. This is crucial as necessary details about the patient and the requested procedure is recorded. This step concludes with an automatically generated order that is transferred to the sonographers including patient demographics, type of procedure and any special instructions from the referring doctor. The patient is then directed to the waiting area until a sonographer becomes available. The patient is called to one of nine ultrasound room depending on availability to commence the diagnosis. Upon completion of the scan, the patient journey will be formally concluded.

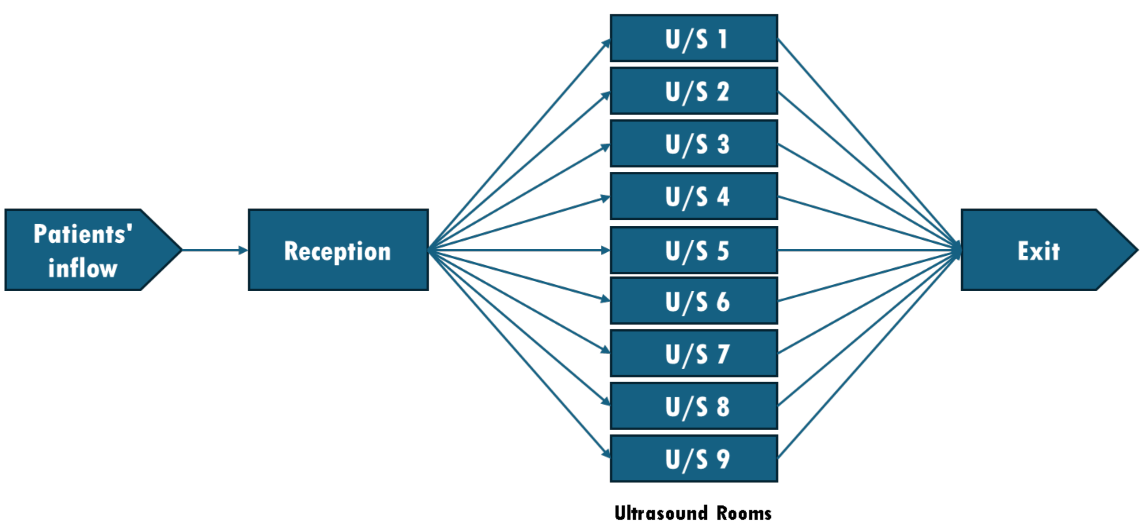

Figure 2. The radiology department conceptual model

The dataset obtained from the hospital consisted of six months historical data on the department activity including procedure types and frequency, patient registration time stamps and duration, procedure time stamps and durations and sonographers shifts and schedules.

The radiology department handles a broad range of diagnostic procedures as shown in Table I. the data obtained initially included 20 types of procedures. However, the 80/20 rule was applied to focus on the most common procedures. The priority analysis revealed that the three most frequent procedures account for around 90% of the department's operations. This includes pregnant uterus ultrasound, pelvic ultrasound and simple pregnancy ultrasound. The simulation study will focus on these operations as they utilize the majority of the department's resources and significantly impact the patients throughput.

Table I .Types of procedures at the radiology department

Procedure Name	Frequency	Percentage	Cumulative
Pregnant Uterus Ultrasound (Fetal & Maternal Evaluation)	10,729	36%	36%
Pelvic Ultrasound	9,444	32%	69%
Simple Pregnancy Ultrasound	6,427	22%	90%
IVF-Vaginal Ultrasound	741	3%	93%
Pelvic Ultrasound Follow-Up (2 Weeks)	690	2%	95%
Transvaginal Echography	443	2%	97%
Others	948	3%	100%
Total	**29,422**	**100%**	

The obtained data representing key simulation input such as patients interarrival times, registration duration and procedure times were analyzed to determine the best fitting statistical distributions. As shown in Table 2. patients interarrival times follow an exponential distribution with a mean of (5.84) minutes. Registration durations follow a Uniform distribution with a minimum and maximum of 1 and 3 minutes respectively. The duration of ultrasound scanning for pregnant uterus, pelvic and simple pregnancy follow an exponential distribution with means of (17.2), (18.5) and (14.9) minutes respectively.

Table 2. Statistical distributions for simulation input data

Input data	Statistical distribution (minutes)
Patients Interarrivals	Exponential (5.84)
Registration process time	Uniform(1, 3)
Pregnant Uterus Ultrasound process time	Exponential (17.2)
Pelvic Ultrasound process time	Exponential (18.5)
Simple Pregnancy Ultrasound process time	Exponential (14.9)

The department operates seven days a week from 8 AM to 10 PM to ensure a continuous availability of services. The current scheduling structure includes two 8- hour shifts per day with an overlap of two hours in between (see Table 3.). Five sonographers work in each shift to manage expected patient volumes and the overlap allows a smoother handover while enabling staff to take essential breaks.

Table 3. Baseline shift schedule and sonographer allocation in the radiology department

Shift	Number of sonographers
8:00 AM - 2:00 PM	5
2:00 PM - 4:00 PM	10
4:00 PM - 10:00 PM	5

The insights from the analysis of obtained dataset will be leveraged to develop a valid simulation model that offers a comprehensive understanding of the current limitations and identifies key areas of improvement. The objective of the simulation study is to optimize patient flow by reducing waiting times and improving resource utilization.

5. Results and Discussion

The baseline model was run for 14 hours over 40 replications to evaluate the patient journey and identify possible improvement initiatives. A total of 140 patients were served at the department, with approximately 40% requiring scanning for a pregnant uterus, 36% for a pelvic scan, and 24% for a simple pregnancy ultrasound.The reception and sonographers seems to be currently underutilized with utilization rates of 34.3% and 49.3% respectively. This is further confirmed by patients waiting times in both processes. On average, patients wait 0.5 minutes at the reception while they wait around 1.3 minutes to be called to the ultra sound room. Figure 3 and Figure 4 show the tracking of average waiting time in reception and ultrasound rooms respectively. In general, the waiting times are low and does not seem to be fluctuating significantly.

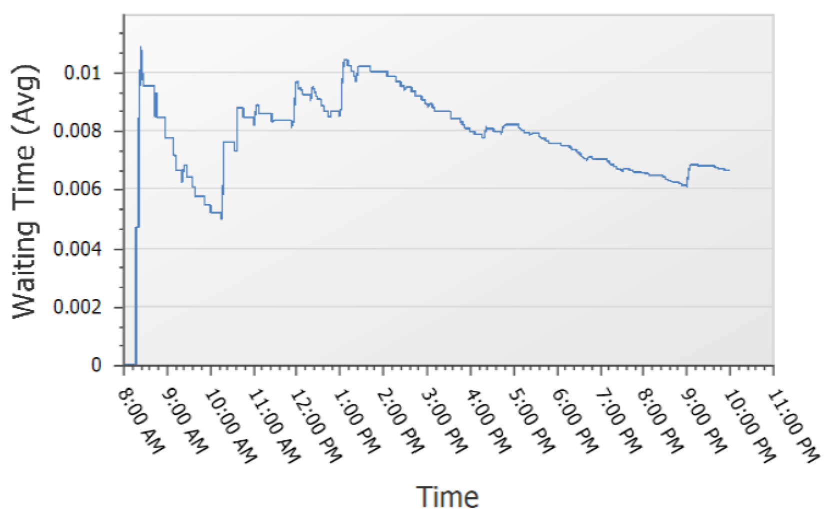

Figure 3. Average patient waiting time at reception

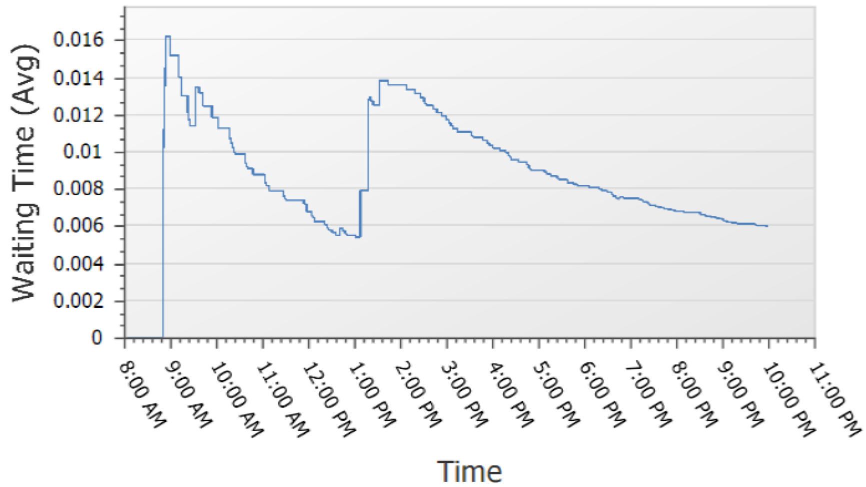

Figure 4. Average patient waiting time at Ultrasound rooms

In light of these results, it may be possible to revisit the allocations of resources to adapt staffing to the demand in the department. Since there is only one staff present at the reception, options to enhance utilization could include merging the service with reception in other adjacent departments, extension of reception responsibilities to include other administrative tasks such as data entry and report management or introducing self-check-in kiosks.

However, the focus of the present simulation study would be on sonographers since they represent the main function in the radiology department. As can be expected, reduction in number of sonographers might have a negative impact on patient waiting times. Therefore, a maximum target average waiting time of 15 minutes has been set for ultrasound diagnostics. In order to assess the number of required sonographers, the average number of utilized sonographers was tracked in one of the replications as shown in Figure 4. It seems that the average utilized sonographers is less than four. Therefore, the first proposed scenario is reducing the number of sonographers per shift to four instead of five while maintaining the shift structure of two 8-hour shifts with an overlap of two hours between shifts. We will refer to this as Scenario 1 : Adjusted Staffing.

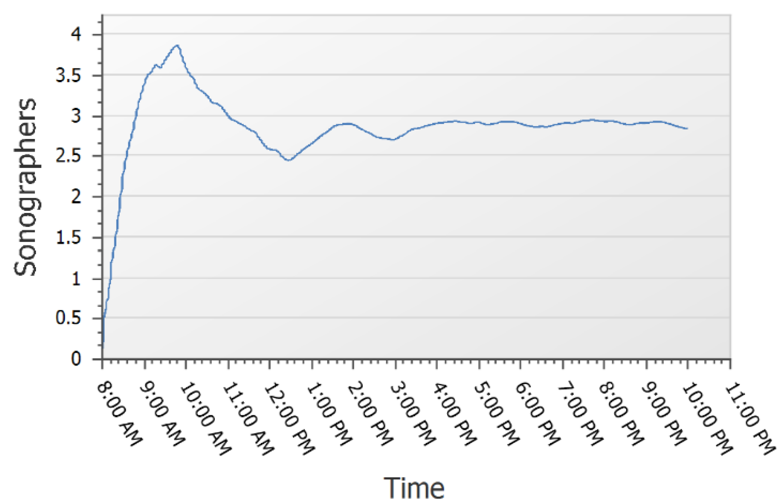

Figure 5. Tracking the Average Number of Utilized Sonographers

In another scenario, It may be worth reconsidering the two-hour overlap since the number of staff is doubled during the overlap despite the low utilization rate. This could be achieved by adopting a dynamic scheduling that allows for shifts to be more flexible and responsive to changes in demand. In the second scenario, a new shorter shifts of two hours are introduced while eliminating the current overlap between shifts. In addition, sonographers can take breaks of up to two hours, allowing for dynamic scheduling. This scenario will be referred to as Scenario 2: Demand-Based Scheduling. A comparison of sonographers staffing across scenarios is shown in Table 4.

Table 4. Comparison of sonographers staffing across scenarios

Shift hours/ scenario	8-10 AM	10-12 PM	12-2 PM	2-4 PM	4-6 PM	6-8 PM	8-10 PM	Number of required Sonographers
Baseline	5	5	5	10	5	5	5	10
Adjusted Staffing	4	4	4	8	4	4	4	8
Demand-Based Scheduling	3	4	4	4	4	3	2	6

Figure 6 presents the results of utilization across scenarios in a box-plot chart. A 95% confidence interval will be used when reporting results in this paper. The utilization of sonographers have increased in Scenario 1:Adjusted Staffing. to 61.1% ±2. While it increased further in Scenario2: Demand-Based Scheduling to 78.2% ±1.6. this constitutes an improvement in utilization over the baseline around of 24% and 60% respectively. The increase in variability of results may be due to the fact that fluctuations in demand will have a greater impact on workload when the number of staff is reduced.

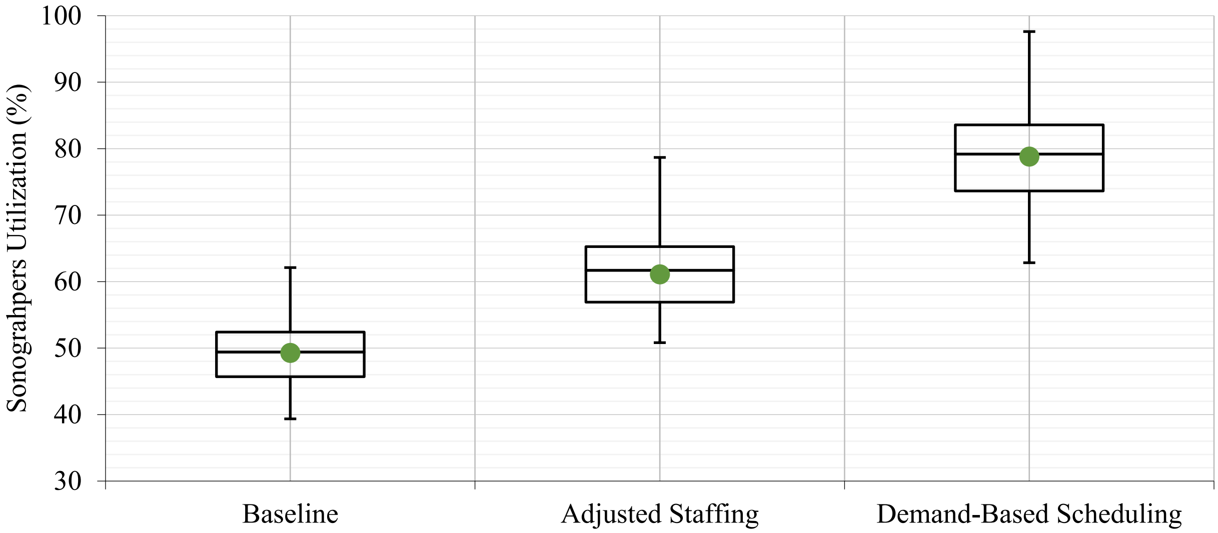

Figure 6. Sonographer utilization across different staffing scenarios

The results of average patient waiting times across scenarios are compared in Figure 7. As expected, the waiting times increased while attempting to improve the utilization rates. In the Adjusted Staffing Scenario, a patient waits an average of 4.7 ±1.1 minutes before an ultrasound room becomes available. In the Demand-Based Scheduling Scenario, patients wait an average of 13.4 ±1.3 minutes. While these results indicate a substantial increase in waiting times compared to the baseline, they remain within the target average waiting time of 15 minutes.

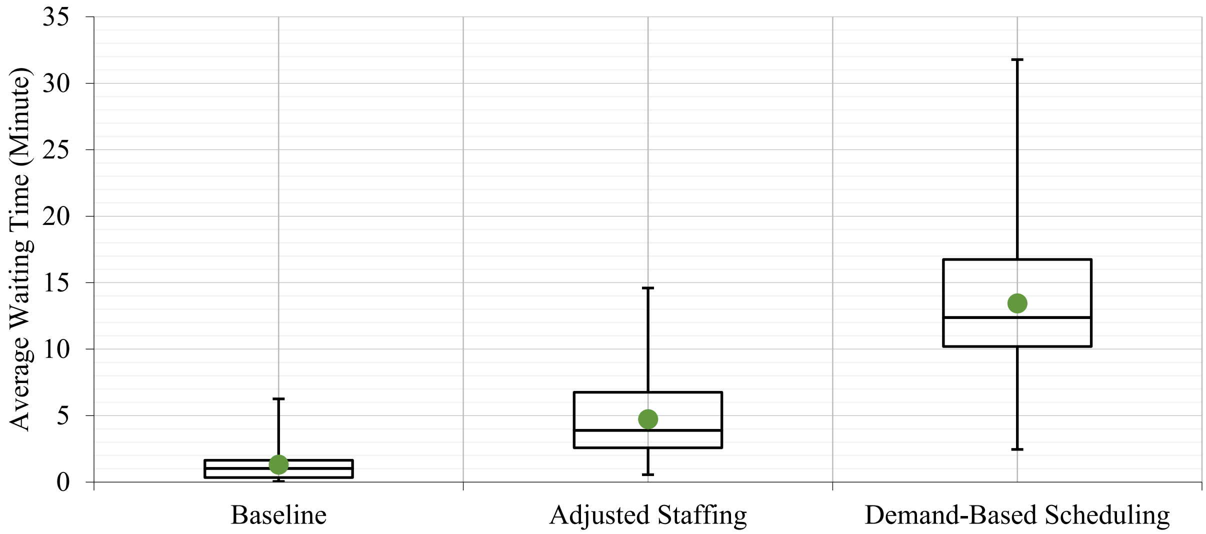

Figure 7. Patient waiting times across different staffing scenarios

Table 5. shows the change of performance metrics across scenarios compared to the baseline. Both utilization rate and cost saving were significantly improved in the two proposed scenarios. However, Scenario 2 performed considerably better than Scenario 1 achieving 60% improvement in sonographers utilization rate and 40% cost saving compared to the baseline. Based on the initial comparison of key performance metrics, Scenario 2: Demand-Based Scheduling seems to be the preferred choice. However, more discussion and analysis will follow to assess its broader implications.

Table 5. Change in performance metrics across staffing scenarios relative to baseline

Scenario	Utilization improvement	Cost saving
1- Adjusted Staffing	24%	20%
2- Demand-Based Scheduling	60%	40%

To analyze the results comprehensively, other factors need to be considered such as scheduling complexity and resistance to change. The fixed structure in Scenario 1 makes it easier to implement as it only requires a reduction of the number of sonographers while keeping the same static shift pattern. In addition, the overlap between the two shifts creates a buffer capacity that can address unexpected demand surges. However, Scenario 1 lacks the flexibility in responding to demand variability with optimized resources.

Table 6. Example of shift schedule under Scenario 2: Demand-Based Scheduling

	8-10 AM	10-12PM	12-2 PM	2-4 PM	4-6 PM	6-8 PM	8-10 PM
Sonographer 1							
Sonographer 2							
Sonographer 3							
Sonographer 4							
Sonographer 5							
Sonographer 6							

Scenario 2 can be more efficient in adapting to changes in the demand while managing costs. As Table 6 shows, the shifts can be altered to accommodate expected increase or decrease in patient arrivals. The allowable gap of two hours within a sonographer's shift further enhance the flexibility of this shift schedule. However, it is more complex to implement since it requires accurate demand forecasting and frequent shift changes.

The changes proposed by both scenarios inherently carry the risk of resistance to change. The anticipated increase in workload further amplifies this risk. This could result in reducing morale and increasing turnover. The flexible scheduling in Scenario 2 may particularly impose an additional burden on staff. Frequent shift changes and having two-hour gaps in the schedule may not be well received by staff. Therefore, a change management program is essential to support the successful implementation of the new scheduling approach.

It is possible to combine both scenarios in a hybrid strategy to maximize long-term benefits while minimizing disruptions to operations. Scenario 1 (Adjusted Staffing) can be implemented first by reducing staff gradually while monitoring patient waiting times and tracking sonographers workloads. This ensures that service levels continue to be within the target range while quantifying the impact on sonographers. A gradual transition to Scenario 2 is recommended following a thorough evaluation of its operational impact and staff adaptability. This can include developing and refining forecasting tools, introducing some shift variations gradually and conducting pilot tests.

In summary, these results show that both scenarios significantly enhance sonographer utilization and cost saving compared to the baseline. Scenario 1 (Adjusted Staffing) is simpler to implement and leads to minimal increase in patient waiting time. On the other hand, Scenario 2 (Demand-Based Scheduling) performs considerably better than Scenario 1 in terms of sonographer utilization and cost saving. However, it introduces scheduling complexity and more change resistance. These finding highlight the need for a balanced approach to implementation.

6. Conclusion

The radiology function serves as a cornerstone of healthcare services, enabling essential diagnosis that underpin patient care. In this study, the operations of radiology were simulated to assess and enhance patient workflow. A tailored simulation model was developed to address the department's needs while focusing on its core function. The analysis of historical data combined with stakeholders input enabled the development of a realistic and valid model. This simulation model allows for evaluating the current workflow to identify key bottlenecks, formulate intervention strategies and test potential scenarios that minimize patient waiting times and improve productivity.

The analysis of the baseline revealed that resources were underutilized with opportunities to enhance the productivity while adhering to waiting times targets. The proposed interventions include: Scenario 1 (Adjusted Staffing) and Scenario 2 (Demand-Based Scheduling). These experiments confirmed that both scenarios improve sonographer utilization compared to the baseline model while average patient waiting times remain within the target level.

The results of Scenario 2 outperformed those of Scenario 1, achieving a 60% improvement in resource utilization and 40% cost savings relative to the baseline model. However, implementing demand-based scheduling introduces greater scheduling complexity and may lead to increased staff resistance. Scenario 1 is easier to implement as it involves a relatively smaller reduction in the number of sonographers while maintaining the existing shift structure. A phased transition strategy is suggested to maximize long-term benefits while minimizing disruptions to operations. The proposed strategy begins with implementation of Scenario 1 while elements of Scenario 2 are incorporated gradually.

While this study provides valuable insights, some limitations should be acknowledged. The analysis relies on historical data assuming stable patient inflow rate, which may not account for sudden unexpected fluctuations such as emergencies with high number of cases. In addition, the model assumes changes to the baseline are applied without significant change resistance, which may not hold true in practice.

A further study could integrate workforce considerations by investigating the relationship between shift structure and length on staff well-being and performance. In addition, future research should focus on empirical validation through assessing the implementation in real-world hospital setting to strengthen the applicability of the findings.

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Biography

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