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An Integrated Framework Using DMAIC, SERVQUAL, Simulation, and MOC to Reduce Waiting Time in Healthcare Systems

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Abstract

Improving any industry requires a comprehensive examination of existing processes to identify inefficiencies and operational bottlenecks. In this study, a healthcare service provider undertook multiple initiatives to enhance its performance but failed to achieve satisfactory outcomes. To address this, industrial engineering tools were employed to drive substantial improvements. The DMAIC (Define, Measure, Analyze, Improve, and Control) methodology was rigorously applied in combination with SERVQUAL, simulation, and MOC techniques to develop an in-depth understanding of the current system and to pinpoint factors contributing to excessive waiting times. Various improvement alternatives were then simulated and assessed to select the most effective solution before implementation. As a result, the system's waiting time was reduced by 55%, while the average number of patients within the system decreased by 39%.

Keywords
DMAIC, SERVQUAL, SWOT, MOC, Simulation.

1. Introduction
Healthy child development is essential for society; however, children are more vulnerable than adults to unfavorable living conditions. Factors such as disease, malnutrition, and poverty have historically contributed to high child mortality rates, with deaths among children under five reaching 12.6 million in 1990 (UNICEF 2018). Overcrowding in emergency departments remains a major operational challenge, leading to prolonged waiting times and patient dissatisfaction. In the pediatric emergency department examined in this study, overcrowding was directly associated with extended waiting times and frequent complaints, with an annual emergency visit volume exceeding 144,000 cases (Anonymous Pediatric Hospital 2022).

In Saudi Arabia, children benefit from strong healthcare systems and targeted national development initiatives. According to the Ministry of Health, substantial improvements were achieved between 1990 and 2012, including a reduction in under-five mortality from 44 to 18.7 per thousand live births, infant mortality from 34 to 16.2, and maternal mortality from 48 to 14 per 100,000 live births (Ministry of Health 2012).

Lean Six Sigma methodologies, particularly the DMAIC framework, are widely used to improve healthcare processes and reduce delays. Previous applications of DMAIC have reported significant reductions in emergency department waiting times and improvements in patient satisfaction (Jacobson et al. 2006; Jun et al. 1999). Discrete-event simulation is also commonly employed in healthcare settings to model system variability and safely test operational changes before implementation (Ahmed and Alkhamis 2009; Hwang et al. 2017).

This paper presents an integrated DMAIC and discrete-event simulation study aimed at: (i) measuring perceived service quality using the SERVQUAL instrument, (ii) developing and validating a simulation model of patient flow, (iii) identifying the primary operational bottleneck, and (iv) evaluating improvement scenarios designed to reduce both the average time patients spend in the system (WS) and the number of patients within the system (LS).

1.1 Problem Statement
With more than 144,000 emergency visits each year, overcrowding during peak periods is a key factor contributing to prolonged waiting times in the emergency department of a pediatric hospital in Taif (Anonymous Pediatric Hospital 2022). This high patient demand leads to delays in medical treatment, reduced overall service quality, and increased dissatisfaction among patients and their families. This study aims to determine the primary factors responsible for extended waiting times and to propose strategies to reduce delays and enhance the efficiency of emergency care services.

1.2 Objectives
The following goals are the focus of this study:

- Analyze patient flow at the hospital by simulating and modeling the current system to find areas that could be improved.
- Find the process bottlenecks that cause long wait times and service delays.
- Provide practical recommendations to address concerns and reduce patient wait times.
- Evaluate the effectiveness of various situations and solutions in terms of delay reduction.
- Optimize hospital staff and essential medical equipment to boost operational efficiency.
- Reduce the anxiety and dissatisfaction that patients experience when they must wait a long period in a hospital.

2. Literature Review

Lean Six Sigma, particularly the DMAIC (Define–Measure–Analyze–Improve–Control) methodology, has been widely applied in healthcare to reduce patient waiting times by identifying the root causes of delays and implementing data-driven improvements. Recent empirical studies indicate that DMAIC-based interventions significantly enhance patient flow and reduce variability in emergency departments, infusion therapy units, and outpatient clinics (Costa et al. 2024; Mistarihi et al. 2023). These findings demonstrate DMAIC's effectiveness in optimizing healthcare processes, achieving notable reductions in waiting times without requiring additional resources.
Patient satisfaction is a critical metric commonly used to evaluate hospital quality and overall performance (Bhattacharyya et al. 2017).

SERVQUAL for service evaluation: The SERVQUAL instrument assesses healthcare service quality by comparing patients' expectations with their actual experiences (Prakash 2010). Hosseinzadeh et al. (2024) applied SERVQUAL in Khuzestan Province during 2022–2023, revealing significant gaps between expectations and perceptions in dimensions such as responsiveness and reliability. Their results underscore the importance of targeted quality improvement initiatives to enhance patient satisfaction and overall service delivery.

Waiting time: Reducing emergency department wait times directly improves patient outcomes and satisfaction. For example, shorter wait times for patients with chest pain in a US emergency department were associated with a significant decrease in mortality rates (Prakash 2010).

Matrix of Change (MOC): The MOC is a tool designed to address concerns related to feasibility, sequencing, location, pace, and stakeholder interests (Hosseinzadeh et al. 2024). Rabelo et al. (2022) incorporated MOC into a Total Quality Management (TQM) framework to link leadership selection with quality-driven organizational transformation. To date, it has not been used in DMAIC projects for assessing or selecting optimal solutions.

Simulation: Simulation is a widely used tool in healthcare that allows researchers to manage variability and uncertainty, evaluate operational changes, and test improvements safely before implementation (Ghanes et al. 2021; Hung et al. 2019).

DMAIC applications: DMAIC has been successfully implemented in hospitals to reduce patient wait times and improve operational efficiency. For instance, Ross (2021) applied DMAIC to identify and address bottlenecks in an emergency department, achieving a 24% reduction in average patient waiting time.

2.1 Research Gap

Despite the widespread use of DMAIC to enhance healthcare and service systems, little research has been done on incorporating several complementary tools, such as SERVQUAL, simulation, and Management of Change (MOC), within the DMAIC framework. Prior research has mostly concentrated on the use of simulation in particular DMAIC phases, with little investigation of its application throughout all phases. Similar to this, MOC has not been methodically integrated into DMAIC, despite being acknowledged as a tool to aid in the selection and implementation of solutions. Furthermore, SERVQUAL's ability to record patient opinions and coordinate process enhancements inside the DMAIC cycle is still underutilized. As a result, there is a gap in the creation and assessment of an integrated framework that simultaneously makes use of simulation, MOC, SERVQUAL, and DMAIC to fully improve system performance and service quality.

3. Methods

This project uses the DMAIC methodology combined with simulation to improve hospital performance and patient satisfaction. DMAIC guides the problem-solving process, while simulation is used to test and evaluate potential improvement solutions (Figure 1).

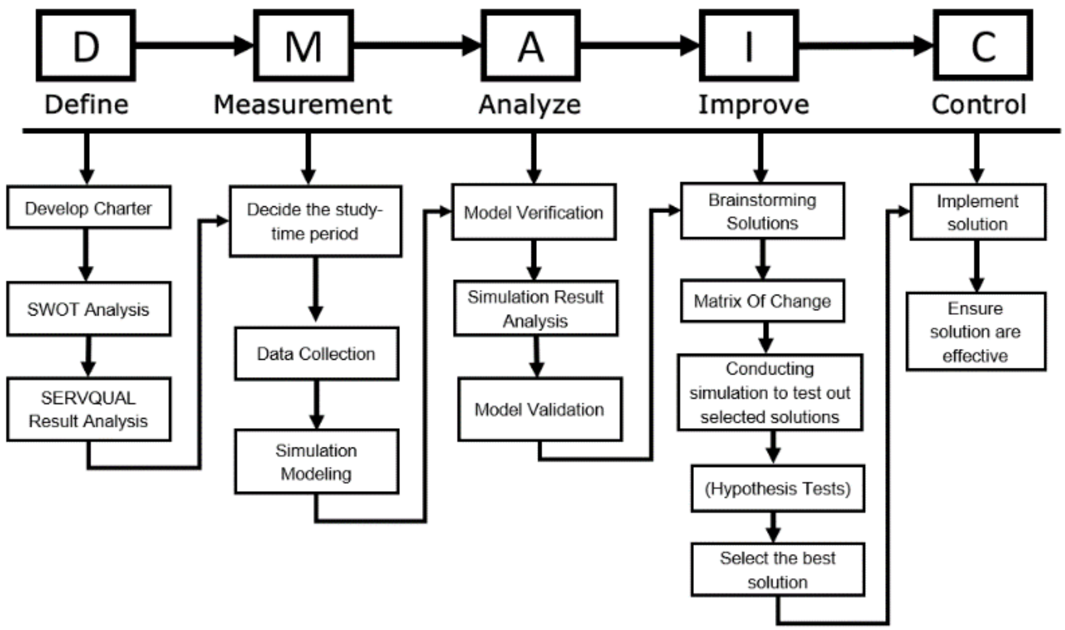

Figure 1. DMAIC Methodology.

Define: This step involves clearly identifying the problem that needs improvement, establishing the objectives of the project, defining its scope, and recognizing the key stakeholders involved.
Measure: In this phase, the current performance of the process is assessed through systematic data collection and analysis to establish a baseline.
Analyze: After measuring performance, the collected data is examined to determine the root causes of inefficiencies or problems within the process.
Improve: Based on insights gained from the analysis, targeted process improvements are designed, tested, and implemented to address identified issues.
Control: Finally, controls and monitoring mechanisms are established to ensure that the implemented improvements are maintained and sustained over time.

3.1 Define Phase

The problem or opportunity for improvement is identified during the DMAIC Define stage. This involves accurately characterizing the problem, establishing clear goals, and identifying the clients and stakeholders affected by the issue. Instead of being used for strategic planning, tools like SWOT analysis are used operationally to assess the emergency department's actual condition. SERVQUAL is used to get patient feedback in order to record the Voice of the Customer. The scope, objectives, direction, and justification for the improvement team's work are all outlined in a project charter (Table 1).

Table 1. SWOT Analysis

Strengths:	***Weaknesses:***
- Hospital location. - Medical skills - The only children's hospital in the area - Well–organized. - MOH Support.	- Shortage of equipment - Parking - The Capacity - Delay in the (blood analysis) department - The number of patient companions - The number of nurses per shift
Opportunities:	***Threats:***
- Improve quality and efficiency. - There are no competitors. - Availability of new technology. - Create healthcare programs.	- Unforeseen emergencies. - Seasonality. - High cost of medical equipment and supplies. - Dealing with a sensitive age group (children).

Following the SWOT analysis, SERVQUAL is applied to assess the difference between customers' expectations and their actual perceptions of the service provided. This tool captures the Voice of the Customer, which is crucial for enhancing service quality and increasing customer satisfaction (Table 2).

Table 2. Data gathering & Analyzing methodology

Description	Methodology Applied	Remarks
Type of Study	Exploratory in nature. Patients were surveyed in the emergency children's hospital in Taif City.	The selection of an emergency children's hospital in Taif was based on the appropriate sampling method.
Sample Size	120 samples	Randomly selected
The collecting data	Collected through a survey by using the SERVQUAL scale.	By using Google forms
Tools for Data Analysis	Microsoft Office Excel	By using a graphical analysis of the collected data.

Table 3 presents the SERVQUAL results collected from 120 patient companions at the pediatric hospital in Taif. The findings indicate that the lowest ratings are primarily associated with waiting times, especially within the Responsiveness dimension. Multiple stages of the patient journey received a significant number of low scores (1 = Very Bad, 2 = Bad), highlighting patient dissatisfaction, as illustrated in Figure 2 and Figure 3.

Table 3. SERVQUAL Results

	1	2	3	4	5	Total
Tangible:						
• Provides advanced medical equipment and equipment	3	7	26	48	36	120
• The suitability and cleanliness of the medical facility and equipment	5	5	24	46	40	120
• The readiness of the waiting areas	11	19	32	27	31	120
Reliability:						
• Extent of follow-up of the patient's condition by the medical staff	3	4	23	46	44	120
• The response of the medical staff to inquiries from patients and their companions	3	6	21	46	44	120
Responsiveness:						
• Waiting time for reception and registration	16	14	28	30	32	120
• Waiting time in the vital signs measurement area	31	20	19	32	18	120
• The waiting period before entering for a diagnosis from a doctor	29	21	29	21	20	120
• The waiting period before entering the observation and health care department	20	15	36	27	22	120
• Waiting time before x-rays (if performed)	4	9	29	19	21	82
• Waiting time to take the analysis sample (if performed)	8	12	29	19	20	88
Assurance:						
• Patients' sense of trust by the medical staff	5	2	21	38	54	120
• The medical staff is patient in dealing with patients	3	6	23	30	58	120
Empathy						
• The extent of the medical staff's personal interest in patients	5	6	26	31	52	120
• Paying attention to health history and previous diseases before dispensing medications	3	6	22	30	59	120
Keys: (1) Very Bad – (2) Bad Acceptable – (3) Acceptable - (4) Excellent – (5) Very Excellent						

As illustrated in Figure 2, 42% of patients reported dissatisfaction with the waiting time before having their vital signs measured, while 16% considered it acceptable.

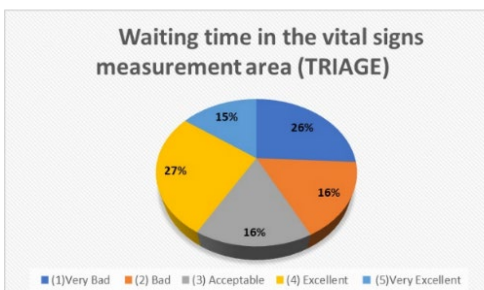

Figure 2. Dissatisfaction about Waiting Time in Vital Signs.

Figure 3 shows that only 35% of patients were satisfied with the waiting time before seeing a doctor, while 41% reported dissatisfaction.

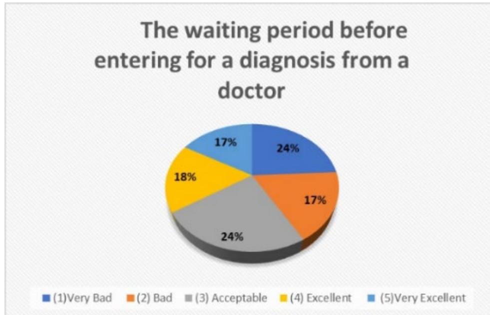

Figure 3. Dissatisfaction with the area before entering the doctor.

3.2 Measure Phase

In the Measure phase, the current performance or baseline of the process is determined by defining the study period, selecting data collection methods, and specifying the simulation approach.

Historical Data:

Historical data from December 2022 obtained from the hospital indicate that the highest proportion of patient arrivals, 43%, occurred between 13:59 and 21:59, representing approximately one-third of the working day, as shown in Figure 4. This peak period corresponds to increased patient flow, resulting in overcrowding in several hospital departments. Consequently, this time frame was selected for data collection and the study (Table 4).

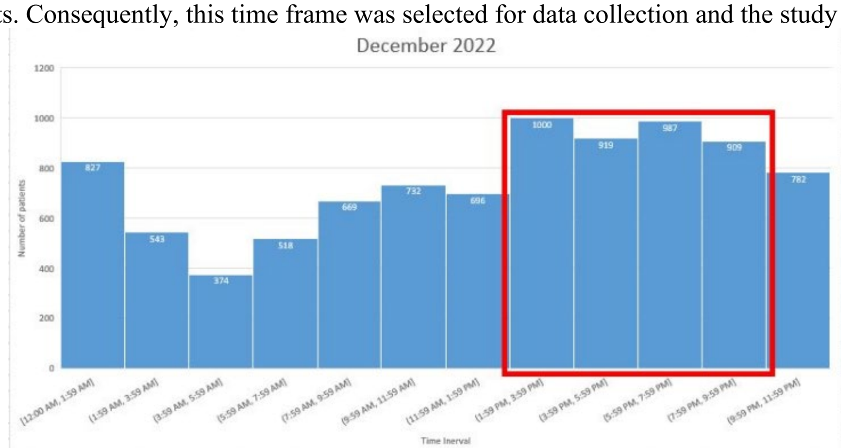

Figure 4. Distribution of patients coming to the hospital.

Table 4. Number of patients coming to the hospital per shift.

Time Window	Number of Patients	% of Total
00:00 - 23:59	8956	—
13:59 - 21:59	3815	43%
21:59 - 5:59	2526	28%
5:59 - 1:59	2615	29%

Data Collection

After choosing the period in which the study will be conducted in the previous section, 84 samples were collected in 7 days of March 2022, which includes the patient's arrival at the hospital until his discharge, and the service time for each of the following (Figure 5 and Figure 6):

- Patient service time in the registration area.
- Patient service time in the vital sign measurement area.
- The time of serving the patient by the doctor.
- Patient service time in the observation area.

Flow Chart of The System:

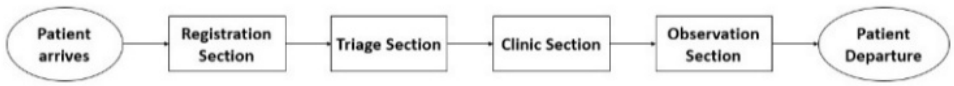

Figure 5. Flow chart for the patient used in modeling.

Levels of patients in the hospital (system):
Patients arriving at the hospital are classified as follows:

Level	Level Description
Level 1	• Life-threatening situations. • Top priority.
Level 2	• Possible life-threatening situations.
Level 3	• It could turn into a serious problem. • It may affect some functions.
Level 4	• Not urgent. • Symptoms but no evidence of deterioration.
Level 5	• Refer Primary Health Care.

Figure 6. Levels of patients.

Table 5. Distribution of Patients by Level

Level	Number of Patients	Percentage of Total Sample
Level 1	0	0%
Level 2	13	15%
Level 3	47	56%
Level 4	24	29%
Total	**84**	**100%**

The above Table 5 summarizes the distribution of patients across the four levels. No patients were recorded at Level 1. Most patients were classified at Level 3, accounting for more than half of the total sample (56%). Level 4 represented nearly one-third of the patients (29%), while Level 2 accounted for the smallest proportion among the recorded levels (15%). This distribution indicates a higher concentration of patients in the moderate to higher levels.

Simulation Modeling
Discrete-event simulation was applied in this project, and the simulation model was developed using Simio software. The exact layout of the hospital was carefully considered during the development of the simulation model. The model was constructed with multiple processes, as illustrated below, where the system structure consists of one source and one sink with four different types of entities. The objects were connected through defined paths, and a selection weight and distance were assigned to each path.

Paths connected the servers, and a selection weight was assigned to each path. The process begins at the registration section, which receives 100% of the patients based on the available data. After registration, all patients proceed to the vital signs section, followed by the doctor section. Finally, patients are classified according to their condition, where 76% are directed to the observation section if required, while the remaining 24% exit the system (Figure 7).

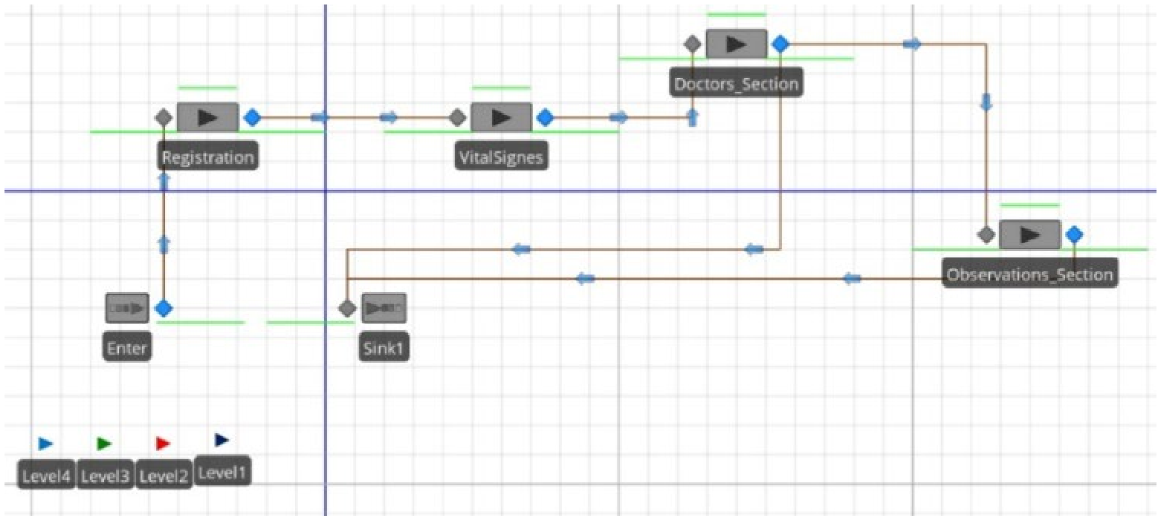

Figure 7. SIMIO Simulation Model.

Model run
The simulation model was run for eight hours, representing a working shift with a one-hour warm-up period, and with ten replications to eliminate variability and reach a steady state.

Model Simulation Verification:
Simulation model verification ensures accuracy by comparing simulation results with analytical solutions that mathematically describe system behavior. These solutions serve as benchmarks to confirm the model's reliability and suitability for predicting real-world performance.

By comparing the results of the simulation model with the predictions of the queuing theory model for the same system. As follows:

1. Assume the arrival rate **λ** for level 3 and service times **μ** as inputs in the queueing theory and simulation model.
2. Calculate the theoretical performance measures: Using queuing theory (Table 6).
3.

Table 6. Queuing theory results for verification

Arrival Rate (per hour) - λ	32			
Server	Registration	VitalSignes	Doctors Section	Observations Section
Capacity	1	1	3	17
Service rate for each server - **μ**	40	60	40	60
Utilization	0.8	0.5	0.8	0.5
Number in Queue	3.2	0.6	3.2	0.6
Number in Station	4.0	1.1	4.0	1.1
Time in Station (min)	7.5	2.1	7.5	2.1
Number in System	10.29			
Time in System (min)	19.29			

4. Run the simulation: Run the simulation model with the same assumed values (Figure 8).

						Scenario1			
Object Type	Object Name	Data Source	Category	Data Item	Statistic	Average	Minimum	Maximum	Half Width
ModelEntity	Level3	[Population]	Content	NumberInSystem	Average	10.4500	9.3511	11.2341	0.4326
			FlowTime	TimeInSystem	Average (Min...	19.5389	17.6681	20.9593	0.7055
Sink	Sink1	[DestroyedEntities]	FlowTime	TimeInSystem	Average (Min...	19.5389	17.6681	20.9593	0.7055

Figure 8. SIMIO Simulation results.

5. Compare the simulation results with the queuing theory predictions (Table 7).
6.

Table 7. Comparing Simulation results with queuing theory

Performance Metrics	Theoretical	Simulation
Number in System (Ls)	10.29	10.45
Time in System (Ws)	19.29	19.53

Based on this, simulation verification was applied to the project, showing that the model is verified as the simulation results align with queuing theory. This increases confidence in the model, enhances prediction accuracy, and reduces the chance of errors.

Model Simulation Validation:
Validation is the process of comparing the simulation model with the real system to ensure its accuracy. In this study, validation was performed using a one-sample t-test, which evaluates whether the mean of the simulation outputs ($\bar{x}$) differs significantly from the hypothesized population mean (μ) obtained from historical hospital data.
The hypotheses are defined as:

$$H_0: \mu = \bar{x} \text{(no significant difference)}$$
$$H_a: \mu \neq \bar{x} \text{(significant difference)}$$

If the p-value ≤ 0.05, the null hypothesis is rejected, indicating a significant difference between the simulation and the real system. If the p-value > 0.05, the null hypothesis is not rejected, suggesting that the simulation model adequately represents the real system. Historical data from the hospital were used as the reference for this validation.

Summary of validation results:

Table 8. Summary result of the hypothesis testing for WS & LS

Patient Level	Time in System (Ws) - Real (μ)	Time in System (Ws) - Simulation ($\bar{x}$)	Result (Time in System)	Number in System (Ls) - Real (μ)	Number in System (Ls) - Simulation ($\bar{x}$)	Result (Number in System)
2	2.5	2.64	Fail to reject H_0 ($p = 0.257$)	10	11.71	Fail to reject H_0 ($p = 0.063$)
3	2.6	2.66	Fail to reject H_0 ($p = 0.357$)	40	42.01	Fail to reject H_0 ($p = 0.373$)
4	2.8	2.93	Fail to reject H_0 ($p = 0.20$)	23	24.5	Fail to reject H_0 ($p = 0.089$)

Based on the one-sample t-test results, there is no significant difference between the sample means and the hypothesized population means (Table 8), indicating that the model is reliable and appropriate for predicting outcomes from the proposed solutions.

3.3 Analyze Phase
After simulation verification, it can be concluded that the simulation results are reliable and valuable. Since simulation allows for interpretation and understanding of complex system behaviors, analyzing these results is a vital step in the simulation modeling process.

Simulation results analysis (Servers):
The results indicate that the average time a patient spends in the vital signs station is 2.64 hours, creating a bottleneck that leads to overcrowding in the waiting line. This results in an average of 81 patients waiting at this station, delaying

the overall patient flow through the system. This situation is primarily caused by a high arrival rate combined with the relatively short processing time at the registration stage (Figure 9- Figure 11).

Server	VitalSignes	InputBuffer	Content	NumberInStation	Average	81.0055
			HoldingTime	TimeInStation	Average (Hou...	2.6478
		Processing	Content	NumberInStation	Average	1.0000
			HoldingTime	TimeInStation	Average (Hou...	0.0664
	Registration	InputBuffer	Content	NumberInStation	Average	0.8098
			HoldingTime	TimeInStation	Average (Hou...	0.0263
		Processing	Content	NumberInStation	Average	0.6383
			HoldingTime	TimeInStation	Average (Hou...	0.0207
	Observations_Section	Processing	Content	NumberInStation	Average	6.5824
			HoldingTime	TimeInStation	Average (Hou...	0.5929
	Doctors_Section	InputBuffer	Content	NumberInStation	Average	2.3639
			HoldingTime	TimeInStation	Average (Hou...	0.1362
		Processing	Content	NumberInStation	Average	2.9296
			HoldingTime	TimeInStation	Average (Hou...	0.2014

Figure 9. SIMIO Simulation results.

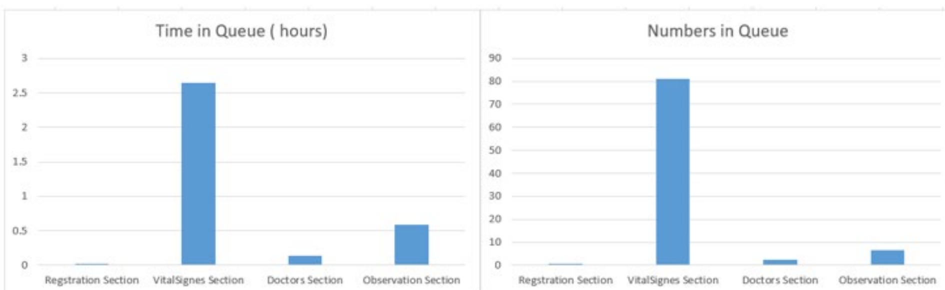

Figure 10. Average Wq, Lq for servers

Simulation results analysis (Patients):

Level4	[Population]	Content	NumberInSystem	Average	30.3217	26.3831	36.8697	2.1869
		FlowTime	TimeInSystem	Average (Hou...	3.2741	2.8568	3.6953	0.1962
Level3	[Population]	Content	NumberInSystem	Average	50.9480	37.9767	63.4619	5.7501
		FlowTime	TimeInSystem	Average (Hou...	3.0425	2.5907	3.3607	0.1882
Level2	[Population]	Content	NumberInSystem	Average	14.2575	10.7882	22.1705	2.4218
		FlowTime	TimeInSystem	Average (Hou...	2.9630	2.4246	3.4065	0.2178

Figure 11. Flow time of patients in the system.

Selected two of them as performance metrics, which are: Time in System W_S, and Number in System L_S (Table 9).

Table 9. Flow time of patients in the system.

Patients Level	Time in System (Ws)	Number in System (Ls)
2	2.96 hours	14.25 patients
3	3.04 hours	50.94 patients
4	3.27 hours	30.32 patients

This indicates patient level 2 takes an average of 177 minutes in the system, Level 3 takes approximately 182 minutes, and Level 4 takes approximately 196 minutes. And 55% of patients are from level 3.

3.4 Improve Phase

The fourth phase of DMAIC is to determine the solutions for the problems identified in the first three phases of DMAIC through:

- Applying Brainstorming techniques to generate solutions.
- Applying the Matrix of Change for choosing corrective action from multiple alternatives.
- Conducting simulation models to test out the chosen solutions.
- Select the solution.

Brainstorming Solution:
Efforts were directed toward identifying strategies to reduce waiting times at the vital signs station after simulation results revealed significant congestion in this area. Brainstorming techniques were applied to generate multiple improvement options, while recognizing that increasing service speed at this stage could lead to bottlenecks in other parts of the process. Consequently, emphasis was placed on balanced interventions that enhance overall system performance and reduce total patient time from arrival to departure.

Following evaluation and prioritization, seven solutions were selected for further assessment using the Management of Change (MOC) framework to identify the most practical and effective approaches for minimizing waiting times and improving patient satisfaction.
The selected solutions include:

- Merging stations
- Increasing staffing levels
- Automating the check-in process
- Rescheduling shifts
- Adding vital signs measurement device
- Improving the waiting area
- Enabling patient registration through a mobile application

Matrix of Change:

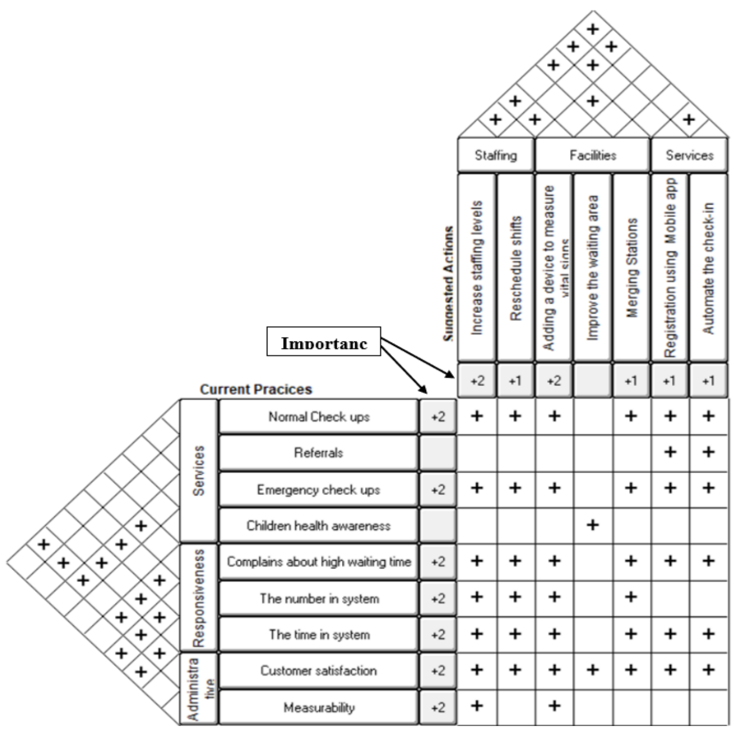

Figure 12. The Matrix of Change.

Figure 12 illustrates the evaluation of the proposed solutions based on their relative importance, as indicated by the number of positive interactions (represented by plus signs) in the transition matrix, considering the importance of each current practice, and the plus signs shown in the upper triangular section of the change matrix. A higher number of plus signs indicates a solution with a greater ability to support or compensate for other solutions.

According to the results obtained from the Matrix of Change tool in Figure 12, the solutions of **increasing staffing levels** and **adding a vital signs measurement device** demonstrated the highest impact, each achieving a total score of seven positive points. Consequently, implementing one or a combination of these two solutions is expected to be the most effective approach.

Simulation Testing of Selected Solutions:

Simulation is used to test the chosen solutions before implementing them in the real world.

The first solution is: Add one more server to the vital signs station by purchasing a vital signs device. From (1 measure vital sign device & 3 doctors) To (2 devices to measure vital signs & 3 doctors).

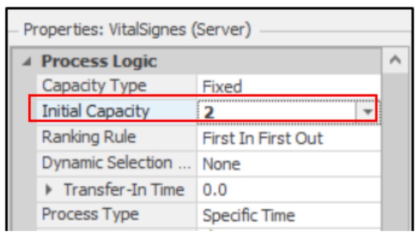

Figure 13. The first solution.

Table 10. First solution results.

Patients Level	Time in System (Ws) - hours	Number in System (Ls)
2	1.14	5.32
3	2.22	37.67
4	0.85	35.31

The second solution is: Add one more server to the doctor's station by hiring a doctor. From (1 measure vital sign device & 3 doctors) To (1 device to measure vital signs & 4 doctors) (Figure 13- Figure 15).

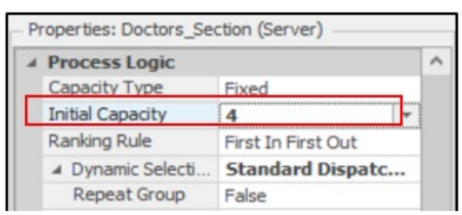

Figure 14. The second solution.

Table 11. Second solution results.

Patients Level	Time in System (Ws) - hours	Number in System (Ls)
2	2.67	12.47
3	2.69	43.75
4	2.64	22.00

The third solution is: Add one more server to both the vital signs and the doctors' station by purchasing a vital signs device and hiring a doctor. From (1 measure vital signs device & 3 doctors) To (2 devices to measure vital signs & 4 doctors) (Table 10- Table 14).

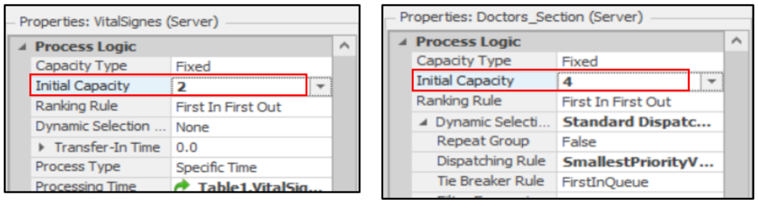

Figure 15. The third solution.

Table 12. Third solution results.

Patients Level	Time in System (Ws) - hours	Number in System (Ls)
2	1.18	5.75
3	1.47	24.06
4	1.32	29.71

Select the best solution:
By using the ratio of each patient level from the collected data, which is demonstrated in Table 13.
Solution 1: The first solution: 2 devices to measure vital signs & 3 doctors
Solution 2: The second solution: one device to measure vital signs & 4 doctors
Solution 3: The third solution: 2 devices to measure vital signs & 4 doctors

Table 13. Patient Ratio.

Sample Size	84	Percentage
Level 2	13	15%
Level 3	47	56%
Level 4	24	29%

Table 14. Select the best solution.

	Time in the System (Ws)			Number in the system (Ls)				
Solution	Ws (L2)	Ws (L3)	Ws (L4)	Ls (L2)	Ls (L3)	Ls (L4)	Sum	Score
Sol 1	1	0	0	1	0	1	3	0.59
Sol 2	0	0	1	0	0	0	1	0.29
Sol 3	1	1	0	1	1	1	5	1.71
Ratio	0.15	0.56	0.29	0.15	0.56	0.29	—	—

Table 14 summarizes the selection of the optimal healthcare configuration by evaluating the performance of each solution across multiple ANOVA tests (F-test) and two-sample t-tests using Minitab software, applied to ten replications of each solution's simulation model results. The evaluation also considered patient-level ratios to account for differences in patient distribution. Solution 1 achieved a total score of 0.59 $(0.15 + 0.15 + 0.29)$, while Solution 2 received the lowest score of 0.29. Solution 3 emerged as the most effective option with a total score of 1.71 $(0.15 + 0.56 + 0.15 + 0.56 + 0.29)$. <u>This top-performing configuration consists of two vital signs measurement devices and four doctors, making it the recommended solution based on the statistical analysis and simulation results.</u>

Cost-benefit of the selected solution:

The recommended solution of adding one doctor and an additional vital signs measurement device has important cost–benefit implications. Although this intervention involves increased operational costs related to staff salaries, equipment purchase, and maintenance, the significant reductions in waiting time and system congestion indicate substantial operational gains. Shorter patient waiting times and lower system occupancy improve patient throughput, reduce overcrowding, and enhance service quality, leading to higher patient satisfaction and better utilization of hospital resources. Furthermore, improved efficiency may reduce indirect costs associated with prolonged waiting, including patient dissatisfaction, staff overload, and potential treatment delays. Therefore, the expected benefits in terms of productivity, service performance, and patient experience are likely to outweigh the additional costs, suggesting that the proposed solution represents a cost-effective investment for hospital management.

3.5 Control Phase

After selecting the best solution and the optimal scenario, the results were statistically validated, confirming that the most effective improvement strategy consists of adding a vital signs measurement station and hiring an additional doctor. This solution demonstrated positive outcomes by reducing patient waiting time, time in the system, and the number of patients in the system, thereby improving the overall efficiency of the emergency department.

The Control phase aims to sustain the improvements achieved during the Improve phase and ensure that the reduction in waiting time is maintained over the long term. To achieve this, periodic audits and performance reviews are recommended to enable hospital management to monitor system performance, identify deviations from target waiting times, and implement corrective actions on time. Additionally, continuous staff training and awareness programs should be implemented to reinforce adherence to the improved workflow and operational procedures.

Key performance indicators (KPIs) must be used to track system stability and efficiency, including average patient waiting time, time in the system, number of patients in the system, and patient satisfaction levels. These indicators should be measured regularly.

Table 15. Control phase KPIs.

KPIs Category	**KPIs**
Time-based KPIs	• Average patient waiting time • Door-to-doctor time • Time in the system (Ws) • Vital signs measurement time per patient
Flow & congestion KPIs	• Number of patients in the system (Ls) • Queue length at the vital signs station • Throughput (patients treated per hour) • Bedroom occupancy rate • Patient arrival-to-service ratio
Resource utilization KPIs	• Doctor utilization rate (%) • Vital signs station utilization (%) • Staff-to-patient ratio per shift
Patient-centered KPIs	• Patient satisfaction score • Number of waiting-time-related complaints

Finally, patient feedback should be collected routinely to evaluate perceived waiting times and overall service quality (Table 15). This feedback acts as an early warning mechanism for potential process deterioration and supports data-driven decision-making, ensuring the sustainability of improvements in emergency department efficiency.

4. Results and Discussion

Improved simulation model results:

Table 16. Best solution results.

Patients Level	Time in System (Ws) - hours	Number in System (Ls)
Level 2	1.18	5.76
Level 3	1.47	24.06
Level 4	1.32	29.71

This indicates patient level 2 takes an average of 70 minutes in the system, Level 3 takes approximately 88 minutes, and Level 4 takes approximately 79 minutes (Table 16).

Comparing the basic model and the improved model:

Table 17. Basic model and improved model results.

Patient Category	Indicator	Basic Model	Improved Model	Percentage Decrease
Level 2	Waiting Time (Ws)	2.96	1.18	60%
Level 2	Number in System (Ls)	14.25	5.75	59%
Level 3	Waiting Time (Ws)	3.04	1.47	52%
Level 3	Number in System (Ls)	50.94	24.06	53%
Level 4	Waiting Time (Ws)	3.27	1.32	60%
Level 4	Number in System (Ls)	30.32	29.71	2%

Summary of Improvements

As shown in Figure16 and Figure 17 and documented in Table 17, the implementation of the optimal solution led to substantial operational gains:

- **Level 2 Patients:** Experienced a **60%** reduction in total time spent in the system and a **59%** decrease in the average number of patients present.
- **Level 3 Patients:** Both waiting time and the number in the system were cut by more than half, decreasing by **52%** and **53%,** respectively.
- **Level 4 Patients:** While the waiting time dropped significantly by **60%**, the average number in the system saw a more modest decrease of **2%**.

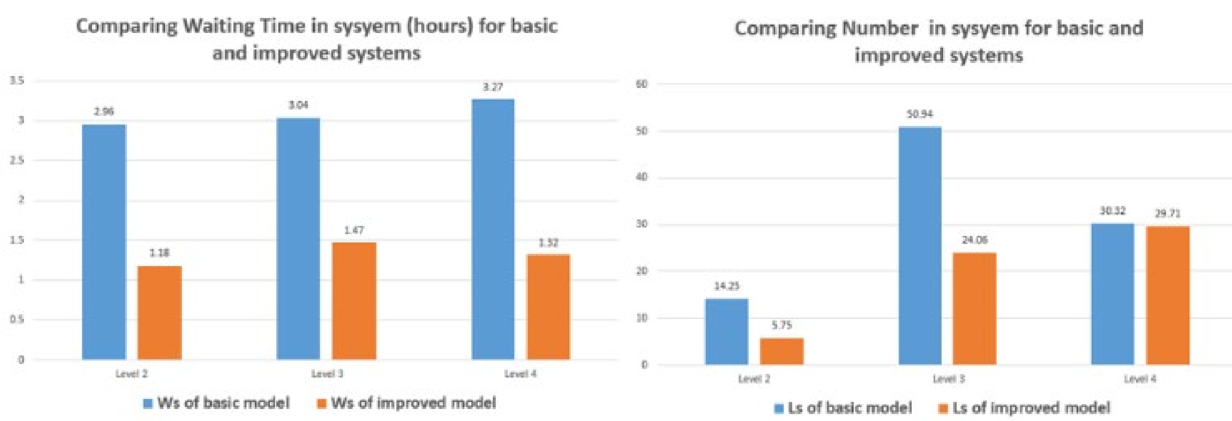

Figure 16. Comparing Ws, Ls for basic and improved systems.

Figure 17 shows the effectiveness of the solution in resolving the bottleneck in vital signs and reducing waiting time in line for the servers.

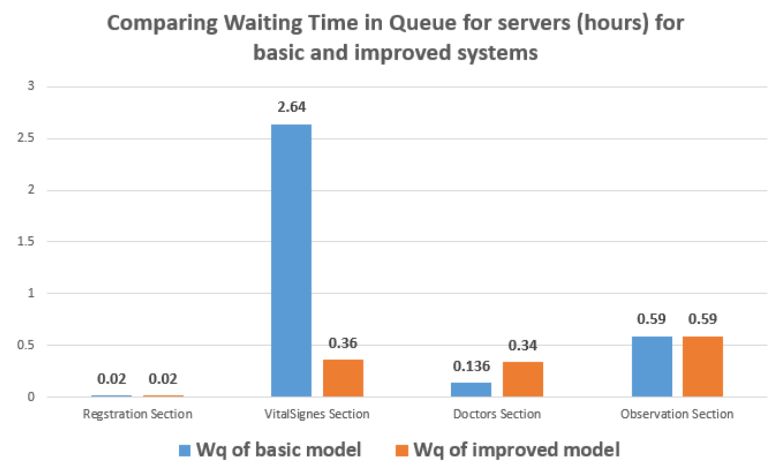

Figure 17. Comparing Wq for the basic and improved systems.

7. Limitation and Future Work

This study has several limitations that should be acknowledged. First, the spatial scope was confined to a single hospital, which may limit the generalizability of the findings to other healthcare settings with different patient volumes, workflows, or resource availability. Second, the temporal scope was restricted to data collected over a one-month period within the last three years, which may not fully capture seasonal variations, fluctuations in patient demand, or longer-term operational trends.

Future research could address these limitations by expanding the study across multiple hospitals to enhance external validity and allow for comparative analysis. Longitudinal data collection over an extended period would also provide deeper insights into temporal patterns and system performance. Additionally, future studies could investigate the implementation of automated patient registration systems using self-service devices integrated with vital signs measurement, evaluating their effects on workflow efficiency, patient throughput, and staff workload. The influence of waiting area design on patient satisfaction and perceived service quality also warrants further exploration. Finally, conducting a comprehensive cost–benefit analysis of the proposed solution would be valuable to assess its financial feasibility, potential cost savings, and return on investment for healthcare institutions.

8. Conclusion

This study identified prolonged waiting times as a major challenge in the emergency department of a children's hospital in Taif Governorate. To address this issue systematically, the DMAIC framework was applied, integrating SWOT analysis, SERVQUAL, Matrix of Change (MOC), and simulation modeling.

SWOT analysis and SERVQUAL evaluation revealed that 42% of patients were dissatisfied with waiting times before vital signs measurement. Data from 84 patients were collected and used to develop and validate a simulation model, which showed that the average patient time in the system ranged from 2.96 to 3.27 hours across patient levels. The main cause of delay was congestion at the vital signs station due to insufficient service capacity.

During the improvement phase, multiple solutions were generated and evaluated using MOC, which played a key role in prioritizing alternatives and identifying the most impactful and balanced solution. MOC analysis pinpointed capacity expansion at the vital signs station as the most effective intervention. Simulation and statistical testing confirmed that the optimal configuration involved adding two vital signs measurement devices and four doctors.

The improved model resulted in a 55% reduction in average time spent in the system and a 39% reduction in the average number of patients present. Waiting times decreased by 60% for Levels 2 and 4 and by 52% for Level 3, with substantial reductions in system occupancy for Levels 2 and 3. Overall, the integrated use of SWOT, SERVQUAL, MOC, and simulation within the DMAIC framework proved effective in reducing waiting times, improving patient flow, and enhancing operational efficiency, while maintaining hospital anonymity.

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