

Optimizing Patient Flow in the Outpatient Departments of Bangladeshi Public Hospitals Using Arena Simulation and the Elimination of Non-Value-Added Tasks

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Received: September 11, 2026; **Accepted:** September 16, 2026; **Published:** September 30, 2026

ABSTRACT

This research addresses the chronic challenge of patient overcrowding and operational inefficiency within the Outpatient Departments (OPDs) of Bangladeshi government hospitals. By employing Arena-based Discrete Event Simulation (DES), this research pinpoints major operational delays by simulating the unpredictable nature of patient entry and treatment durations. A baseline analysis revealed that peak-hour demand surges of approximately 700% result in 100% resource utilization at manual registration counters, leading to operational gridlock and a 400% escalation in non-productive wait times. To mitigate these delays, the study integrates Lean principles and Value Stream Mapping (VSM) to identify and eliminate Non-Value-Added (NVA) activities. A digital intervention, the "Swift Health Hospital Queue Optimizer," was developed to transit a manual registration to an online triage and appointment scheduling framework. Consequently, post-implementation simulation results demonstrate a transformative 53.40% reduction in average total patient journey time and an 82.61% decrease in NVA time. Furthermore, system throughput more than doubled, showing a 101.8% increase in patients processed. Validated across three distinct healthcare facilities, these findings provide a robust, evidence-based framework for leveraging technology-driven simulation to enhance healthcare capacity and patient-centricity in resource-constrained settings.

Keywords: Simulation, Non-Value-Added, VSM, DES, Hospitals

Introduction

Long waiting times, patient congestion, and uneven resource utilisation are persistent challenges in healthcare delivery. Patients pass through interconnected stages, including registration, triage, consultation, diagnostic testing, and discharge, where a delay at one service point can affect the entire patient journey. In the Bangladeshi healthcare setting examined in this study, understanding these interactions is essential for identifying bottlenecks and improving the use of available staff and facilities. Simulation offers a practical means of examining alternative service arrangements without disrupting routine operations [1,2].

Discrete event simulation (DES) represents individual patients and the events that change their status within the system, such

as arrival, service initiation, and service completion. It can therefore capture variation in patient demand, service duration, and resource availability. Its suitability for healthcare analysis is supported by reviews documenting applications across operational and clinical settings. Arena provides a platform for implementing these models and comparing the effects of proposed changes on waiting time, queue length, throughput, and resource utilisation [3,4].

Hospital queue improvement requires attention to both service capacity and the organisation of patient flow. Staffing adjustments may relieve a bottleneck, while changes to registration, task allocation, or service procedures may improve performance without a substantial increase in resources. Previous studies have investigated Lean process improvement and technology-supported registration, demonstrating the value of evaluating

Citation: Md. Hasan Ali, Md. Rahad Laskar, Md Imran Hasan, Tahamina Aktar, Mst. Ifrat Ara Tonni. Optimizing Patient Flow in the Outpatient Departments of Bangladeshi Public Hospitals Using Arena Simulation and the Elimination of Non-Value-Added Tasks. J Glob Health Soci Med. 2026. 2(3): 1-11.

DOI: doi.org/10.61440/JGHS.M.2026.v2.60

different intervention types before implementation. However, their results cannot determine which combination will be suitable for the hospital investigated here because demand patterns, patient routes, and available resources differ between institutions [5,6].

This study consequently uses Arena-based DES to identify bottlenecks, compare staffing and resource-allocation alternatives, and support the selection of an appropriate improvement scenario. It also incorporates the “Swift Health Hospital Queue Optimizer,” a digital intervention developed to support the transition from manual registration to online triage and appointment scheduling. The objectives are to reduce waiting times and the number of non-served patients, improve the allocation of doctors, nurses, and operators, and increase patient throughput. Performance will be assessed through a common set of operational indicators, allowing the proposed digital arrangements to be evaluated alongside service capacity.

Related Research

Healthcare Simulation and Model Credibility

Gunal provided guidance on building hospital simulation models and selecting an appropriate modelling approach for the decision problem [1]. Forbus and Berleant reviewed 311 DES studies published between 2017 and 2021, documenting applications in healthcare operations, disease progression, screening, and health behaviour [3]. More recently, Vecillas Martin examined healthcare DES research and the statistical distributions used to represent service processes. Together, these studies establish a methodological foundation for hospital simulation and emphasise the importance of matching model assumptions to the system being investigated. For queue analysis, this requires appropriate representation of patient arrivals, service times, routing, and resource availability, supported by verification and validation [4].

Patient-Flow Improvement and Resource Allocation

Healthcare applications demonstrate how simulation can identify the processes responsible for delays. Werker developed and validated an Arena model of radiation therapy planning, finding that reducing the duration and variability of oncologist-related delays offered the greatest improvement in their setting. Teymourifar used Arena and Process Analyzer to compare emergency-department resource configurations and assess their effects on waiting times and utilisation. Both studies support targeting the activities that constrain patient flow before changing capacity [7,8].

Process redesign provides another route to improvement. Ahmad combined Lean techniques with Arena simulation in a Malaysian outpatient department and reported a simulated reduction of 7.21 minutes, or 15.20%, in average patient processing time after waste elimination and process changes [5]. Kakooei, using data from 3,364 dental hospital patients, showed that rearranging staff duties and introducing parallel service arrangements could improve queue performance without increasing total staffing. These findings support comparing resource reallocation and workflow changes with staffing additions [9].

In Bangladesh, Rahman combined Arena-based patient-flow modelling with scenario analysis and the Analytic Hierarchy

Process (AHP). The reported simulation results indicated that adding two resources while removing one could reduce non-served patients to almost zero. This study demonstrates the practical connection between simulation and structured scenario selection, although the outcome remains dependent on the facility and assumptions represented in the model [2].

Registration and Digital Queue Management

Krisnawati compared manual hospital registration with alternatives supported by applications or machines using Arena DES. Their model incorporated patient registration status and reported a reduction in patient rejection to 1% under the examined configuration. This provides a relevant basis for evaluating digital entry processes. For the present study, a further consideration is whether changes at registration improve the complete patient journey or transfer congestion to consultation and diagnostic services. The proposed online triage and appointment-scheduling arrangements therefore require evaluation alongside downstream resource availability [6].

Complementary Service and Industrial Research

Evidence from other sectors offers relevant analytical perspectives. Samad applied Arena to waiting lines at a CNG filling station, illustrating the use of simulation to examine service queues and waiting-time measures. Ali combined Monte Carlo simulation with linear regression to assess beverage supply-chain performance under uncertainty, providing a complementary example of simulation-supported operational decision-making. These applications inform the treatment of variability and service performance, while hospital models additionally require appropriate patient pathways and priorities [10,11].

Rahman developed a sustainability-oriented TOPSIS framework for supplier evaluation, illustrating how alternatives can be compared transparently against multiple decision criteria [12]. Amin applied K-means clustering to performance data from 550 garment operators, providing an industrial example of data-driven workforce assessment relevant to future investigations of staff-performance differences [13]. Ali used anthropometric measurements of Bangladeshi male sewing operators to propose workstation improvements, offering a complementary perspective for future consideration of worker–workstation compatibility in hospital design. These studies inform scenario evaluation, workforce analysis, and physical design considerations; their industrial findings do not establish the effectiveness of hospital queue interventions [14].

Research Gap

The reviewed studies provide evidence for improvements through targeted staffing, task reassignment, process redesign, and digital registration. However, they do not establish how the proposed Swift Health intervention will interact with staffing and service capacity in the hospital examined in this research. The central gap is therefore the need for a locally grounded assessment that connects patient-entry arrangements with the subsequent stages of care.

Three issues require attention: identifying the bottlenecks that emerge under the hospital’s demand conditions; evaluating the

combined effects of registration changes and resource allocation across the patient pathway; and comparing alternatives using consistent measures of waiting time, queue length, throughput, non-served patients, and utilisation. This defines a specific operational research problem without assuming that findings from another facility will transfer directly. Cost assessment, physical layout analysis, and hybrid simulation remain possible extensions requiring additional data and modelling.

Contributions of The Study

The study is designed to contribute a hospital-specific Arena model for diagnosing patient-flow bottlenecks, a consistent framework for comparing staffing and resource-allocation scenarios, and a simulation-based assessment of the proposed Swift Health Hospital Queue Optimizer. Linking these elements supports practical decisions about how to coordinate patient entry with available service capacity. The contribution remains focused on the original objectives of reducing delays, limiting non-served patients, and improving resource utilisation; the extent of improvement will be established by the model validation and scenario results.

Methodology

The study applies Discrete Event Simulation (DES) in Arena software to model and improve the hospital queue system. Patient arrival rates, service times, and resource data were collected and used to build a baseline model of current operations. The model was validated against real hospital data to ensure reliability. Finally, different scenarios such as fast-track queues and resource adjustments were tested to evaluate their impact on reducing waiting times and enhancing patient flow efficiency.

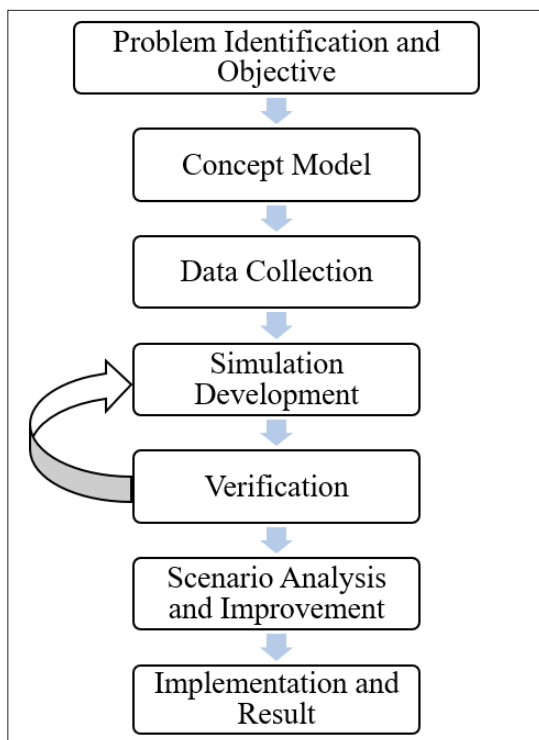


Figure 1: Methodological Framework of the Proposed Model

Problem Identification and Objective Setting

Begin by identifying the core problem, such as long waiting times and inefficient patient flow. Define clear objectives, which

typically include optimizing patient flow, reducing waiting times, eliminating bottlenecks, and maximizing resource utilization.

Conceptual Modeling and Process Flow Description

Create a conceptual model as a blueprint, independent of specific simulation software (Arena). This helps in understanding the problem situation, defining objectives, and identifying system boundaries, inputs, outputs, and interacting elements. Develop a detailed workflow or process flow diagram of patients within the healthcare system, such as an outpatient department or clinic. This involves mapping all stages from patient arrival to departure. Simplify complexity by framing hospital operations, dividing them into manageable parts, and aggregating some processes.

Data Collection and Statistical Analysis

Collect quantitative data through observation (e.g., using stopwatches for service times) and existing records (e.g., patient arrival times, patient numbers, queue lengths, waiting times, discharge rates). Gather qualitative data through interviews with healthcare staff and authorities to understand processes, challenges, and decision-making criteria. Perform statistical analysis of the collected data using tools like Arena Input Analyzer to identify appropriate probability distributions (e.g., Uniform, Triangular) for patient arrival rates and service times. This is crucial for building credible models.

Simulation Model Development

Utilize Discrete Event Simulation (DES), which is widely recognized as a powerful method for modeling dynamic, stochastic systems with strong queuing structures, especially in healthcare. Implement the model using Rockwell Arena Software (or Arena version 14), which is frequently cited for its flexibility, visual representation capabilities, and tools for input and output analysis. The DES model should include Entities and Attributes typically patients, with attributes like arrival time, admission time, and discharge time. Resources such as doctors, nurses, beds, and equipment. Network of processes defining how entities interact with resources and flow through the system. Variables Both inputs and outputs for model logic and performance measurement.

Verification and Validation (V&V)

Ensure the simulation model accurately represents the real system. This involves verifying that the model's logic and code are correct and validating that the model's output behavior is consistent with the real system's behavior. This process might involve engaging multiple experts for complex hospital models.

Improvement Implementation (Lean Techniques)

Develop and analyze alternative scenarios in the Arena Process Analyzer or similar tools to evaluate potential improvements without affecting real patient care or requiring significant monetary investments. Integrate Lean techniques to identify and eliminate waste (e.g., waiting, motion, transportation, over-processing, defects) in the process flow. Examples include, adding resources (e.g., more counters, staff, doctor rooms) rearranging staff duties or establishing parallel service lines. Relocating layouts to reduce unnecessary patient and staff movement. Implementing improved registration systems (e.g.,

web/application-based registration) to reduce waiting times and patient refusal.

Data Analysis and Findings

This chapter presents the results of the Discrete Event Simulation (DES) used to evaluate the operational efficiency of the hospital system. By utilizing Arena simulation software, a baseline model was constructed from real-world data to pinpoint the exact sources of systemic gridlock and provide a foundation for evidence-based improvements.

Purpose of the Simulation Analysis

The primary goal of this analysis is to provide a comparative briefing of how the hospital performs under varying demand levels. The simulation allows for a detailed examination of Assessing the system's ability to scale output (throughput) in response to massive increases in patient arrivals. Quantifying the "non-productive" time patients spend waiting versus the Value-Added (VA) time spent receiving actual care. Identifying specific stations, such as registration counters or diagnostic departments, that become overwhelmed during surge periods.

Model Fidelity and Reliability

To ensure the findings are credible, the simulation followed a rigorous Verification and Validation (V&V) process. Real data on patient arrival patterns and service times were processed through the Arena Input Analyzer to identify appropriate statistical distributions, ensuring the virtual model mirrors actual hospital operations. The model's logic and code were tested to ensure they accurately represent the complex interactions between patients, staff, and medical resources.

Analytical Framework

The analysis is structured to compare two distinct operational scenarios: Off-Peak Time and Peak Time. This comparison highlights how a 700% increase in patient arrivals during peak hours leads to a 100% utilization of resources like "Operators," causing the system to reach a state of operational gridlock. By tracking individual entities (patients) as they move through the network, the simulation quantifies critical Key Performance Indicators (KPIs), including average waiting times, queue lengths, and work-in-progress (WIP) levels, which are detailed in the following sections.

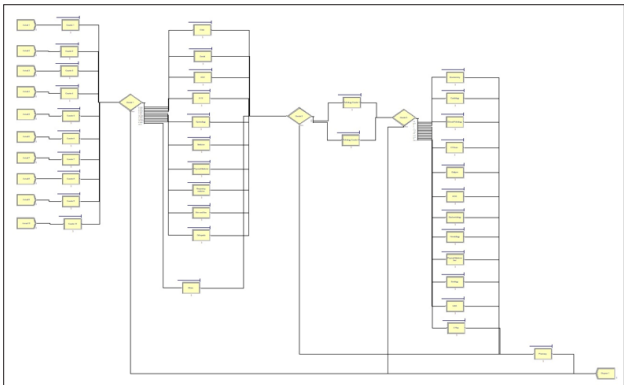


Figure 2: Simulation model of OPD Hospital 1 (before implementation)

System Performance Analysis

This briefing provides a comparative analysis of system performance under two distinct operational scenarios: an "Off-Peak Time" and a "Peak Time" condition. The analysis reveals that the system is severely over-capacitated during peak periods. The primary system bottleneck is unequivocally identified at the ten "Counter" stations, which are managed by the "Operator" resource. During peak times, Operator utilization reaches 100%, leading to massive queues where the average number of waiting patients skyrockets from near-zero to over 110 per counter. While this initial constraint is the most severe, other key resources, including "Doctors," "Pathologists," and "Pathology Operators," also operate at near-maximum utilization levels in both scenarios, indicating secondary or latent system constraints. The data strongly suggests that the current system design and resource allocation are inadequate to handle peak demand, leading to significant operational gridlock and a severely degraded patient experience.

System Performance Comparison

The fundamental disparity between the two scenarios is the system's inability to scale its output to match the massive increase in input demand during peak times. While patient arrivals increase by 700%, patient departures (throughput) increase by only 27%, causing the system to become saturated with patients awaiting service. Table 4.1 shows this Comparison.

Table 1: System Performance Comparison

Key Performance Indicator	Off-Peak Time Scenario	Peak Time Scenario	Percentage Change
Average Patient Arrivals (Number In)	379.25	3040.50	+701.8%
Average Patient Departures (Number Out)	222.50	282.50	+27.0%
Average Work-in-Progress (WIP)	76.05	1344.45	+1667.9%

Patient Journey and Experience Analysis

The systemic congestion during the peak scenario directly translates into a significantly prolonged and degraded patient experience. The average total time a patient spends in the system nearly quadruples, with the increase almost entirely attributable to a 400% surge in non-productive wait time. Value-added (VA) service time remains relatively constant between the two scenarios.

Table 2: Comparison of Patient Waiting and Service Times: Peak vs. Off-Peak

Patient Time Metric (Average)	Off-Peak Time Scenario	Peak Time Scenario	Absolute Change
Total Time in System	0.3284	1.2947	+0.9663
Wait Time	0.2438	1.2143	+0.9705
Value-Added (VA) Time	0.0718	0.0675	-0.0043
Non-Value-Added (NVA) Time	0.0116	0.0122	+0.0006
Transfer Time	0.0009	0.0006	-0.0003

The table shows a substantial increase in patient time metrics during peak hours compared to off-peak periods. The total time in the system rises sharply from 0.3284 to 1.2947, mainly driven by a significant increase in waiting time, which accounts for the largest absolute change (+0.9705). In contrast, value-added (VA) time slightly decreases during peak hours, indicating that the actual service time remains almost unchanged. Non-value-added (NVA) time shows a marginal increase, while transfer time slightly decreases. Overall, the analysis indicates that congestion during peak periods primarily affects waiting time rather than service efficiency, highlighting waiting time as the key area for improvement during peak hours.

System Bottlenecks and Queue Analysis

The analysis of queue data pinpoints specific operational areas that are overwhelmed during the peak time scenario. The "Counter" queues emerge as the primary and most severe bottleneck, though congestion cascades throughout other departments.

Primary Bottleneck: Counter Queues

The ten initial service counters experience an exponential increase in congestion, moving from a state of negligible waiting to one of extreme overload. This is the source of the system-wide gridlock.

one. This indicates severe congestion during peak times and suggests that patient demand greatly exceeds service capacity across the system during these periods.

Secondary Congestion Points

The initial bottleneck causes knock-on effects, with significantly increased queues and waiting times observed in numerous clinical and diagnostic departments. The most impacted areas are listed below.

Table 4: Secondary Bottlenecks: Average Patient Wait Times by Department.

Department Queue	Average Number Waiting (Off-Peak)	Average Number Waiting (Peak)	Average Wait Time (Off-Peak)	Average Wait Time (Peak)
Skin and Sex	5.0382	19.4358	0.2142	0.5414
Hematology	6.8679	13.4002	0.5028	0.8351
Medicine	2.9581	11.6835	0.2168	0.5077
X Ray	5.7768	8.5113	0.3548	0.7389
Gynecology	1.8329	8.1121	0.2135	0.4886
Biochemistry	12.7815	12.5555	1.0694	0.9564
Clinical Pathology	3.7126	4.9064	1.1849	0.0000

Resource Utilization and Staffing Analysis

The resource utilization data confirms the sources of the system's bottlenecks. The "Operator" resource becomes fully saturated, while other critical staff operate at near-maximum capacity, indicating little to no buffer to handle surges in demand.

Table 5: Resource Utilization Comparison

Resource	Average Utilization (Off-Peak)	Average Utilization (Peak)
Operator	63.75%	100.00%
Doctor	99.06%	99.41%
Pathologist	96.43%	96.48%
Pathology Operator	96.36%	88.26%
Pharmacist	63.34%	80.32%
Others Doctor	13.41%	26.96%

Table 4.5 illustrates a system under significant pressure, particularly among specialized medical staff. Doctors and Pathologists are operating

Table 3: Average Number of Patients in Queue: Peak vs. Off-Peak Comparison

Queue Name	Average Number Waiting (Off-Peak)	Average Number Waiting (Peak)
Counter 1	0.0362	119.41
Counter 2	0.0143	115.89
Counter 3	0.0220	112.71
Counter 4	0.0270	123.12
Counter 5	0.0435	118.07
Counter 6	0.0382	110.58
Counter 7	0.0428	122.25
Counter 8	0.0300	114.14
Counter 9	0.0347	114.43
Counter 10	0.0460	108.96

The table shows a very large difference in queue lengths between off-peak and peak periods at all counters. During off-peak hours, the average number of patients waiting is almost zero for every counter, indicating efficient service with no congestion. In contrast, during peak hours, queues increase sharply at all counters, with more than 100 patients waiting on average at each

at critical capacity, maintaining over 96% utilization regardless of peak or off-peak status, leaving almost no margin for emergencies or rest. During peak periods, the Operator reaches a maximum capacity of 100%, representing a clear bottleneck in the workflow. Interestingly, while most roles see increased demand during peak hours, the Pathology Operator experiences a slight decline, and the "Others Doctor" remains significantly underutilized, suggesting a potential imbalance in how tasks are distributed across the facility.

Improvement & Implementation

This chapter details the operational transition from a manual, counter-based registration system to a digital workflow using the Swift Health Hospital Queue Optimizer. By applying Lean techniques and Value Stream Mapping (VSM) principles, the implementation specifically targets the elimination of Non-Value-Added (NVA) time, such as the physical wait times at counters that can exceed 2.76 hours. The digital intervention aims to restructure the patient journey, moving the registration and triage processes online to ensure that patients only enter the physical facility for Value-Added (VA) clinical services.

Working Procedure of Swift Health

The Swift Health Hospital Queue Optimizer follows a streamlined five-step digital process designed to bypass traditional physical counter queues and save users approximately 165 minutes of waiting time.

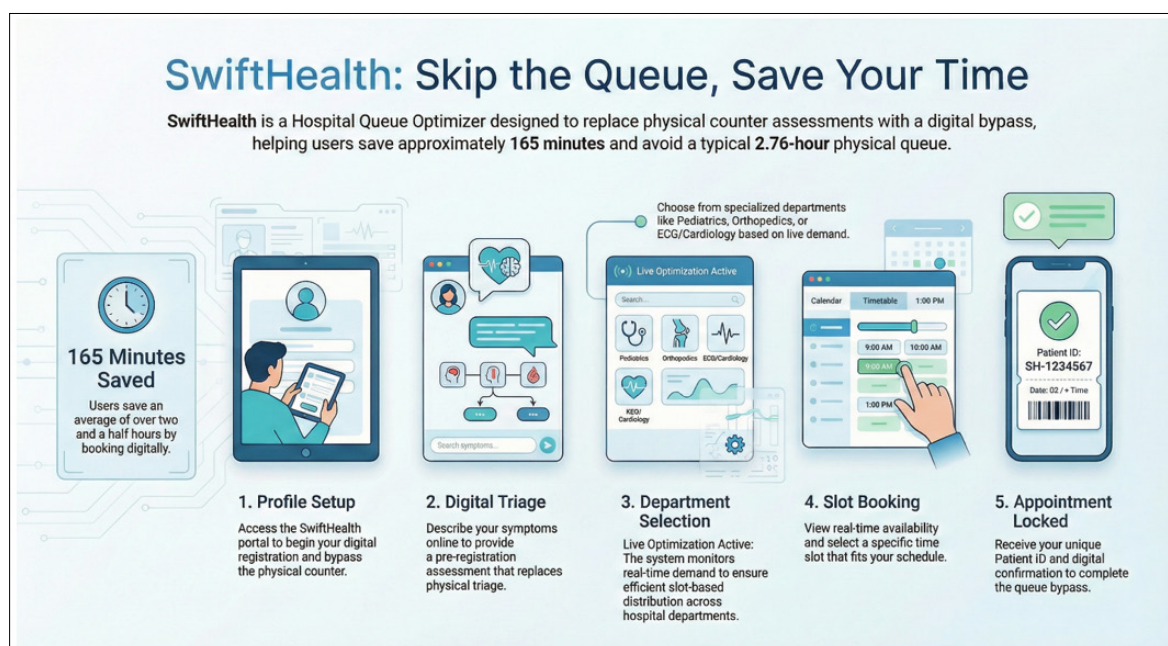


Figure 3: Working procedure of Swift Health

Profile (Authentication)

The process begins with the user logging into their existing Swift Health account or signing up for a new one. This step allows patients to skip counter queues that can last over 2.76 hours by moving the registration process online.

Triage (Digital Registration)

In this stage, the user completes a Digital Triage & Registration form.

- **Symptom Description:** Users describe their symptoms or reasons for the visit in a dedicated text box.
- **Efficiency:** This digital input replaces the physical counter assessment.
- **Constraint:** To maintain the efficiency of the slot-based system, emergency overrides are disabled during this step.

Department (Specialty Selection)

Users select the specific medical department they require. The system displays real-time live optimization data, including:

- **Demand Levels:** Categorized as "Low", "Medium", or "High" demand.
- **Wait Times:** An estimate of how many patients are currently waiting (e.g. 8.45 waiting for Pediatrics).
- **Available Specialties:** Options include Pediatrics, Orthopedics, ECG / Cardiology, and ENT Specialists.

Slots (Appointment Selection)

Patients select a specific appointment time from a list of available slots. The interface clearly marks times that are "Fully Booked" and shows the remaining capacity for others (e.g., "2/2 slots left"). Users also have the option to go back and change the department if necessary.

Done (Confirmation)

The final step "locks" the appointment and confirms that the user is registered digitally. The system generates a specific Patient ID

(e.g., SH-4429) and displays the confirmed department, completing the counter bypass.

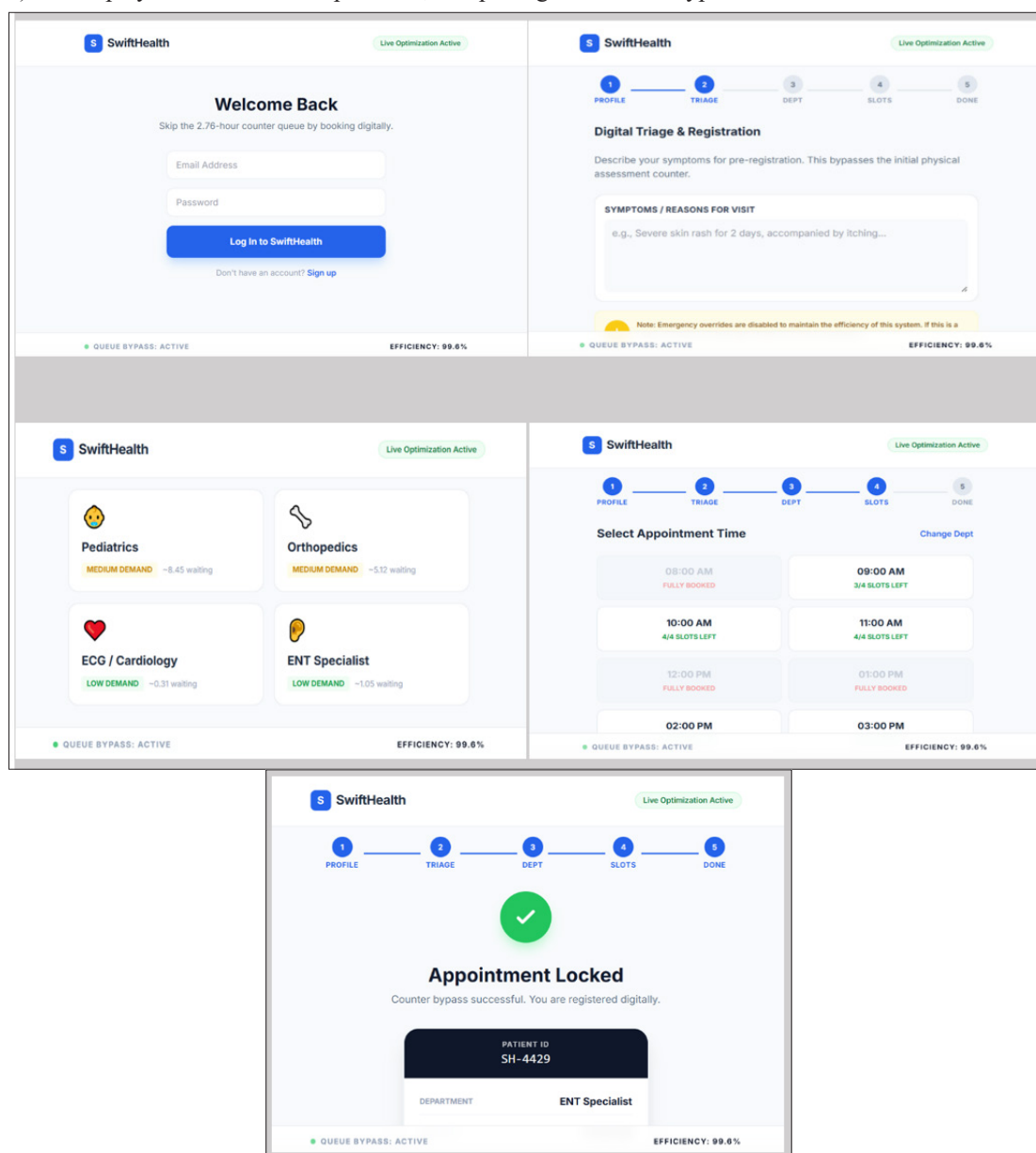


Figure 4: Different Interface of The Application

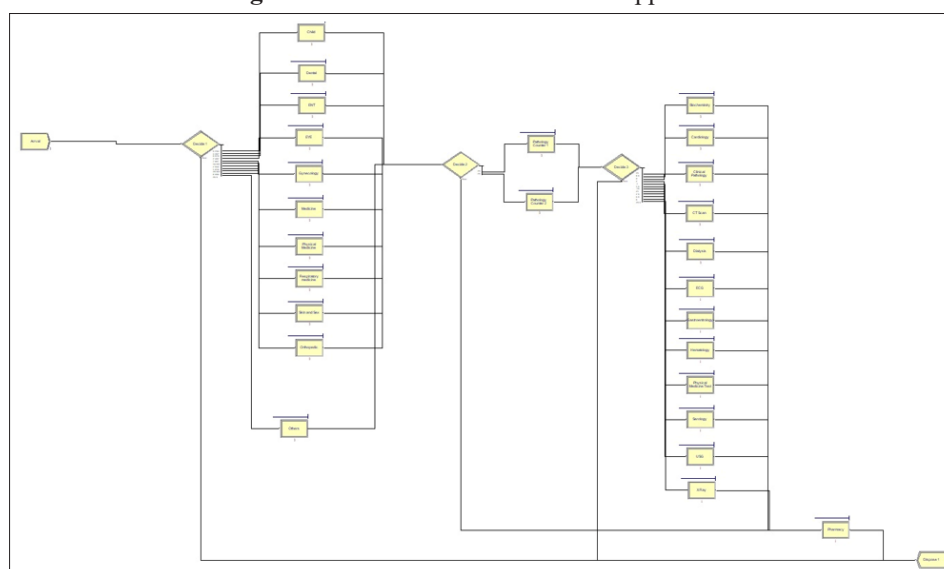


Figure 5: Simulation model of OPD Hospital 1 (after implementation)

The implementation resulted in a dramatic improvement in system throughput, with the average number of patients processed ("Number Out") more than doubling from 283 to 571. This was achieved alongside a major reduction in the patient's total time in the system, which decreased by over 53% from an average of 1.34 hours to 0.62 hours.

Results and Discussions

The results of the Discrete Event Simulation (DES) used to evaluate the operational efficiency of the hospital system and the impact of the proposed digital interventions. By utilizing Arena simulation software, the study identifies systemic bottlenecks and demonstrates how a digital queue optimizer can significantly improve patient flow.

Change of Overall System Performance and Patient Flow

The most significant impact of the implementation is the substantial increase in system throughput. The average number of patients processed per 3-hour replication more than doubled, indicating a major enhancement in overall system capacity. While the number of patients entering the system remained comparable, the work-in-progress (WIP) saw a slight reduction.

Table 6: Overall System Performance and Patient Flow

Key Performance Indicator	Pre-Implementation (Average)	Post-Implementation (Average)	Percentage Change
Patient Number Out	283	571	+101.8%
Patient Number In	3040.50	3035.75	-0.16%
Patient Work-In-Progress (WIP)	1344.45	1190.15	-11.48%

Change in Patient Journey Time

The implementation led to a dramatic reduction in the time each patient spends in the system. The average total time was more

than halved. This improvement is primarily driven by a more than 50% reduction in average wait time. Value-added (VA) and non-value-added (NVA) times were also significantly reduced. Notably, transfer time was completely eliminated in the post-implementation scenario.

Table 7: Patient Journey Time Analysis Post-Implementation scenario.

Time Component	Pre-Implementation (Avg. Hours)	Post-Implementation (Avg. Hours)	Percentage Change
Total Time	1.3353	0.6223	-53.40%
Wait Time	1.2476	0.5758	-53.85%
VA Time	0.0731	0.0441	-39.67%
NVA Time	0.0138	0.0024	-82.61%
Transfer Time	0.0008	0.00	-100.00%

Change in Resource Utilization

The implementation triggered a fundamental restructuring of resource allocation and usage. The "Operator" role appears to have been eliminated, while the "Others Doctor" role has become critical and operates at near-full capacity. The utilization of most other professional resources like "Doctor," "Pathologist," and "Pharmacist" increased to nearly 100%.

Table 8: Scheduled Utilization Post-Implementation

Resource	Pre-Implementation (Avg. Utilization)	Post-Implementation (Avg. Utilization)	Change
Operator	100.00%	0.00%	-100%
Doctor	99.41%	99.90%	+0.49%
Pathologist	96.48%	96.73%	+0.25%
Pathology Operator	88.26%	97.87%	+9.61%
Pharmacist	80.32%	97.53%	+17.21%

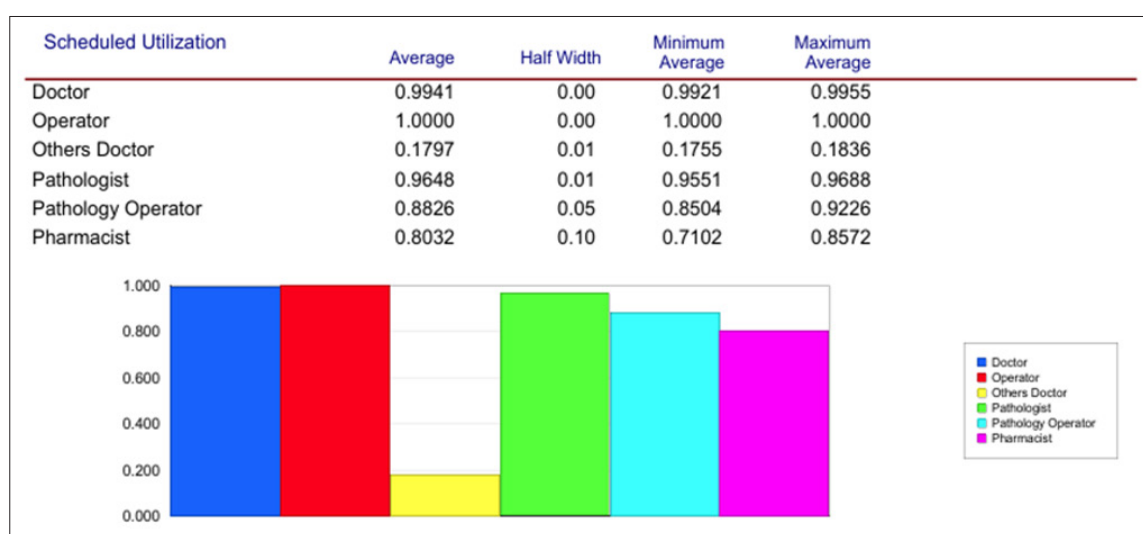


Figure 6: Resources utilization pre-implementation

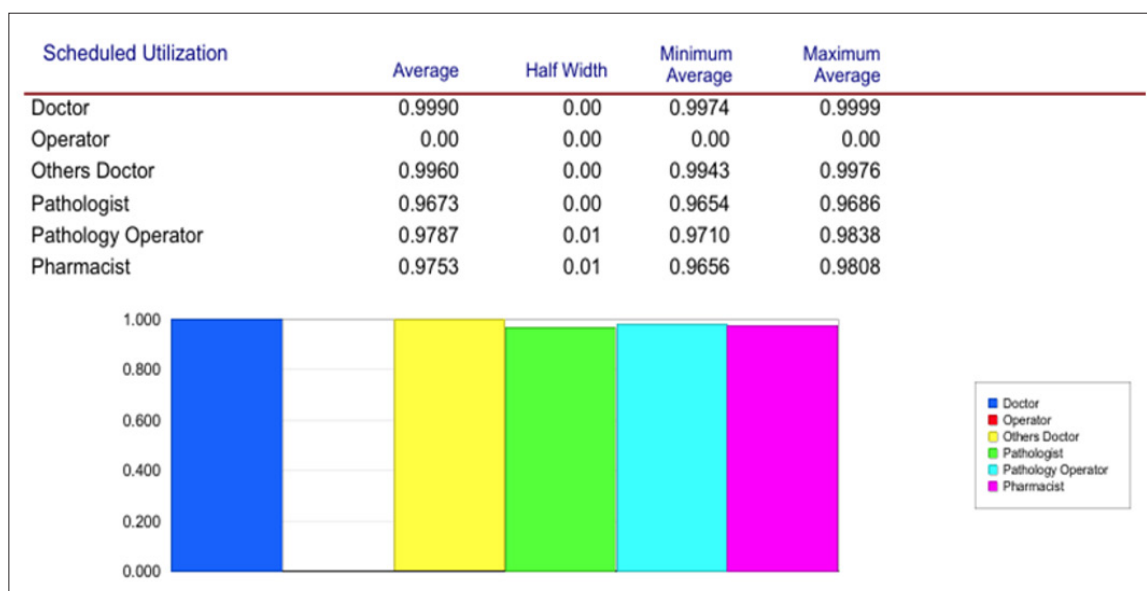


Figure 7: Resources utilization post-implementation

Evaluation of System Outcomes

To further validate the results established in the primary analysis of Hospital 1, this section examines the performance of Hospital 2 and Hospital 3 before and after the software implementation. The data across both facilities confirms a consistent trend of improved operational efficiency following the intervention. Specifically, both hospitals saw an increase in patient throughput, with Hospital 3 showing a significant rise in the System Number Out from 163 to 252.

A critical finding in both cases was the dramatic reduction in Non-Value Added (NVA) time, which decreased from approximately 0.0213 to 0.0036 in Hospital 2 and from 0.0213 to 0.0035 in Hospital 3. This reduction in waste directly contributed to a decrease in the Average Total Time patients spent in the system for both facilities. While the Value Added (VA) time remained relatively stable, the overall Wait Times also showed a downward trend after the software was introduced. The table below provides a detailed comparison of these Key Performance Indicators (KPIs) for both hospitals.

Table 9: Hospital 2 and Hospital 3 Performance

Metric	Hospital 2 (Before)	Hospital 2 (After)	Hospital 3 (Before)	Hospital 3 (After)
KPI: System Number Out	124	128	163	252
VA Time (hr)	0.1026	0.1004	0.1010	0.0996
NVA Time (hr)	0.02129709	0.00363790	0.02129938	0.00351277
Wait Time (hr)	1.1916	1.1821	1.3073	1.2715
Total Time (hr)	1.3155	1.2862	1.4297	1.3746

Discussion

The results of this study unequivocally demonstrate the power of Discrete Event Simulation using Arena to diagnose and solve complex patient flow problems in Bangladeshi hospitals. The baseline analysis confirms the literature's assertion that healthcare systems are prone to bottlenecks and long waiting times, particularly under high demand. The identification of the administrative "Counter" as the primary bottleneck aligns with the thesis objective of pinpointing specific operational areas causing gridlock.

The proposed "Swift Health Hospital Queue Optimizer" proved to be a highly effective intervention. By digitizing the registration and triage process, the solution eliminated the primary bottleneck, which directly aligns with lean principles of removing non-value-added activities. This intervention led to a more than 100% increase in patient throughput and a 53% reduction in total patient time, successfully achieving the core

objectives of reducing waiting times and optimizing resource utilization. The shift in resource utilization from administrative operators to clinical staff represents a significant improvement in efficiency, ensuring that skilled medical professionals are engaged in value-added activities. The findings mirror those of studies like Krisnawati et al. which found that digital and machine-based registration systems dramatically reduce waiting times and patient refusal [6].

The validation across two other distinct hospitals suggests that the digital front-end solution is a robust and generalizable strategy for improving patient flow in similar healthcare settings. The consistent reduction in NVA time and total system time across all three facilities provides strong evidence for its effectiveness.

While the operational improvements are significant, this study shares a limitation noted by Rahman in the Bangladeshi context: the absence of a cost-benefit analysis. Future research should

integrate economic data to provide a more holistic evaluation for hospital administrators. Nonetheless, this thesis provides a clear, evidence-based framework for leveraging simulation to implement impactful, technology-driven solutions that enhance the efficiency, capacity, and patient-centricity of healthcare delivery in Bangladesh [3].

Conclusion

This study confirms that Discrete Event Simulation (DES), implemented in Arena, is an effective approach for diagnosing and improving patient flow in Bangladeshi hospitals. The findings show that severe systemic congestion emerges under peak demand, where patient arrivals increased by approximately 701.8% while patient departures (throughput) increased by only 27%, leading to excessive work in progress (WIP) and substantial delays throughout the system. The manual registration counters, operated by the “Operator” resource, were identified as the primary bottleneck, with operator utilization reaching 100% and queue lengths increasing exponentially during peak demand. These conditions caused a disproportionate rise in patient waiting times and reduced overall service efficiency.

The study further demonstrates that the introduction of the Swift Health Hospital Queue Optimizer, which digitizes registration and triage, can significantly improve system performance. The intervention reduced the average total time in the system by 53.40% and non-value added (NVA) time by more than 82%, while throughput (Number Out) more than doubled. This indicates that substantial improvements in system capacity can be achieved without a corresponding increase in physical resources. Moreover, replication of the intervention in two additional facilities showed consistent reductions in NVA time and total time in system, suggesting that the proposed digital queue optimization strategy is scalable across different hospital types and settings.

Overall, this study contributes to both healthcare operations research and practical hospital management. It reinforces Arena based DES as a robust decision support tool for evaluating “what if” scenarios without disrupting live operations, demonstrates how Lean principles can be integrated with simulation to identify and eliminate non-value-added activities, and provides context specific evidence for the Bangladeshi hospital setting. In addition, the design and evaluation of the Swift Health Hospital Queue Optimizer offer a structured and replicable framework for digital registration and scheduling in similar healthcare environments. Taken together, the findings support the broader adoption of simulation guided and technology enabled process redesign to reduce waiting times, alleviate congestion, and improve service efficiency in resource constrained healthcare systems.

Limitations & Recommendations

Despite its strengths, the study is subject to several limitations that should be acknowledged. First, model scope and system complexity remain important concerns, as the DES model does not capture every clinical and administrative interaction within the hospital. As a result, some inter departmental dependencies and rare events may therefore be under represented, which can limit the granularity of certain inferences. Second, the absence

of economic evaluation is another limitation. Due to a lack of reliable cost data, the study did not conduct a formal cost benefit or cost effectiveness analysis of the digital intervention. Consequently, the financial feasibility and payback period of the proposed solution remain unquantified. Third, limited patient segmentation also affects the analysis. Patients were not stratified by type (e.g., new vs. returning, emergency vs. routine). Therefore, differences in pathways, service times, and priorities among these subgroups were not fully explored in the simulation model. Finally, data collection constraints must also be considered. The construction and calibration of the model depended heavily on manual data collection (e.g., direct observation and timing). Such methods are time consuming and vulnerable to measurement error, which may introduce some uncertainty into parameter estimates. Taken together, these limitations suggest that, while the conclusions are robust at a system level, further refinement and additional data would allow for more detailed and context sensitive analyses.

It is advisable to implement digital registration and scheduling systems that include online triage, appointment allocation, and real-time demand visibility. Furthermore, hospital management have to use DES consistently to evaluate changes in staffing, structure, and patient routing prior to adoption. Simultaneously, Lean thinking must be integrated into process redesign by eliminating non-value-added tasks. Ultimately, digital queue optimization must be expanded and tailored across facilities with localized parameter calibration. Future studies should integrate detailed cost data to conduct comprehensive cost benefit or cost effectiveness analyses, enabling evidence-based investment decisions in digital infrastructure. Subsequent models should explicitly incorporate the physical layout of facilities, the routing of patients, and flows of equipment and materials, with the goal of minimizing travel distances, congestion points, and spatially induced delays. Researchers are encouraged to explore hybrid models that combine DES with System Dynamics or Agent Based Simulation to better capture feedback loops, patient behavior, and multi-unit interactions in large hospitals. Future simulations should differentiate between key patient categories (e.g., emergency vs. elective, new vs. follow up, age groups), allowing the design of tailored queuing policies such as priority rules, dedicated fast tracks, or differentiated service windows.

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