**Journal of Systems Thinking in Practice**
**JSTINP, *QUARTERLY***
**Homepage: jstinp.um.ac.ir**
**Online ISSN: 2821-1669, Print ISSN: 2980-9460**
**Research Article**
DOI: 10.22067/JSTINP.2026.96638.1190
JSTINP 2026; Vol. 5, No. 2

# Improving Patient Waiting Time in the Emergency Department Using System Dynamics Modeling (Case Study: Kosar Hospital, Semnan)

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***How to cite this article***

Zarei, A., Ebrahimi, M. and Sadat Kia, E., 2026. Improving Patient Waiting Time in the Emergency Department Using System Dynamics Modeling (Case Study: Kosar Hospital, Semnan), *Journal of Systems Thinking in Practice*, *5*(2), pp.26-49. doi: 10.22067/jstinp.2026.96638.1190.

URL: https://jstinp.um.ac.ir/article_48191.html.

**ABSTRACT**

The emergency department, as one of the most critical components of the healthcare system, constantly faces challenges such as crowding and prolonged patient waiting times. These issues not only increase staff workload but can also reduce the quality of care and patient satisfaction. Given the necessity of improving emergency department performance, system dynamics modeling serves as an effective tool to understand system behavior under varying conditions and to evaluate the impact of managerial and operational interventions. The aim of focuses on policy-based improvement rather than formal mathematical optimization, using system dynamics simulation to evaluate alternative intervention scenarios.

The study began with a systematic review of scientific literature and prior experience related to emergency department management and patient waiting time reduction. Subsequently, semi-structured interviews were conducted with key experts—including physicians, nurses, and hospital managers—to identify the factors influencing patient flow and waiting time. Based on these findings, a system dynamics model was developed and simulated in Vensim. Three managerial and operational scenarios were designed: controlling patient arrival rates and increasing triage capacity, improving workforce effectiveness by enhancing physician-to-patient and nurse-to-patient ratios, and a combined scenario involving the simultaneous implementation of all interventions. The results revealed that the combined scenario produced the greatest improvement, leading to a substantial reduction in the overall average waiting time.

Overall, the findings indicate that the simultaneous implementation of managerial and operational interventions yields the greatest synergistic effect and can serve as an effective strategy to optimize emergency department performance, reduce congestion, and enhance the quality of hospital services.

***Keywords***

System dynamics modeling, Patient waiting time, Emergency department, Hospital performance improvement, Managerial policies, Quality of healthcare services.

***Article history***

Received: 2025-11-22
Revised: 2026-04-15
Accepted: 2026-05-11
Published (Online): 2026-06-20

**Number of Figures: 7** **Number of Tables: 4** **Number of Pages: 24** **Number of References: 25**

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## 1. Introduction

The growing demand for services in hospital emergency departments, coupled with hospitals' limited operational capacity, represents one of the most critical challenges facing healthcare systems worldwide. The emergency department plays a vital role in delivering immediate care and ensuring patient safety under critical conditions. However, high patient volume, inpatient bed shortages, and process inefficiencies have made the average waiting time and length of stay in the emergency department key indicators of care quality and safety (Lauque et al., 2023). Extensive research has demonstrated that prolonged waiting times and extended stays are associated with adverse clinical outcomes, including increased patient withdrawal before receiving care, decreased patient satisfaction, and increased mortality risk. Therefore, reducing the average waiting time in emergency departments is not merely an operational objective but also a pressing public health necessity (Sartini et al., 2022).

The phenomenon of crowding in hospital emergency departments is typically examined across three domains: input (patient arrivals), throughput (service processes such as triage, laboratory testing, and imaging), and output (patient discharge or transfer to inpatient wards). Studies indicate that one of the most significant contributors to prolonged patient length of stay in emergency departments is the practice known as boarding a situation in which patients, despite having been approved for admission to inpatient beds, remain in the emergency department. This condition substantially reduces the department's operational capacity (Ansah et al., 2021; Mohr et al., 2020).

Despite the availability of various research approaches such as regression analysis, discrete event simulation, and machine learning models for predicting emergency department length of stay, system dynamics, which applies stock and flow diagrams and causal loop diagrams, has been introduced as an appropriate framework for understanding the nonlinear and feedback relationships among input, throughput, and output factors. This approach enables the development of a holistic model of patient flow and allows for policy experimentation, such as modifying staff shift schedules, implementing fast track pathways, reducing laboratory turnaround times, or adding short stay beds. Moreover, software tools such as Vensim provide researchers with the capability to construct transparent, implementable, and replicable models and to evaluate the effects of policies within a safe environment (Ansah et al., 2021; Mehrolhassani et al., 2025).

In many hospitals, the average waiting time and patient length of stay in the emergency department exceed acceptable thresholds or target benchmarks, such as 4 or 6 hours. This situation results in consequences including reduced quality of care, increased pressure on staff, a higher likelihood of medical errors, and even elevated risks of mortality (Lauque et al., 2023). Although numerous studies have examined individual factors such as patient age and physician diagnosis, process-related factors such as triage duration and laboratory turnaround times, and organizational factors such as the number of available beds and staffing levels, most have analyzed these determinants separately or used static statistical methods. Few studies have considered nonlinear interactions, feedback mechanisms, and time delays, or employed policy-oriented modeling approaches (Payne et al., 2023; Farimani et al., 2024).

Moreover, in many countries, including Iran, evidence indicates that contextual factors such as nurse shift structures, interdepartmental admission processes, access to paraclinical services, and referral policies play a crucial role in influencing patient length of stay. However, there is a scarcity of studies that apply a system dynamics approach to examine these factors and provide a comprehensive analysis of proposed policies (Mousavi Kashani and Zargar Balaye Jame, 2024; Abasi Niasar et al., 2024).

Table 1 presents the factors contributing to the increase in average patient waiting time in hospital emergency departments, compiled from a review of domestic and international literature.

Table 1. Factors influencing the increase in average patient waiting time in emergency departments

| No. | Variable | Definition / Mechanism of impact on waiting time | References |
|---|---|---|---|
| 1 | Patient arrival rate | A higher arrival rate leads to system overload and queue formation; when input exceeds capacity, waiting times increase. | (Ansah et al., 2021; Siddiqui et al., 2025) |
| 2 | Triage level / disease severity | Patients with higher priority are admitted more quickly; variations in case severity explain differences in average waiting times. | (Wang et al., 2024; Lauque et al., 2023) |
| 3 | Number of staff (physicians/nurses) and skill mix | Staff shortages or an inappropriate skill mix create bottlenecks in clinical processes; increasing staff numbers or optimizing shifts reduces delays. | (Ansah et al., 2021; Zhang et al., 2021) |
| 4 | Inpatient bed capacity and patient boarding | Limited inpatient beds force admitted patients to remain in the ED, occupying space and resources and increasing waiting times for new arrivals. | (Ayenew et al., 2024; Lauque et al., 2023) |
| 5 | Laboratory and radiology turnaround times | Delays in test and imaging results slow down decision-making and prolong the length of stay. | (Ayenew et al., 2024; Lauque et al., 2023) |
| 6 | Triage and registration processes | Slow triage or registration creates queues at entry; interventions to streamline triage shorten the time to first medical contact. | (Davari et al., 2024; Alhabib et al., 2024) |

| No. | Variable | Definition / Mechanism of impact on waiting time | References |
|---|---|---|---|
| 7 | Clinical pathways and care protocols | Clearly defined care pathways and protocols for common cases prevent unnecessary repetition and waiting. | (Alhabib et al., 2024) |
| 8 | Mode of arrival | Patients arriving by ambulance often present higher priority and complexity; the distribution of arrival modes affects waiting times. | (Wang et al., 2024) |
| 9 | Day, time, and seasonality | Peak hours, holidays, and specific times of day influence demand and shape queuing patterns. | (Ansah et al., 2021; Siddiqui et al., 2025) |
| 10 | Diagnostic complexity | Patients requiring multiple tests, imaging, or specialist consultations have longer stays. | (Ayenew et al., 2024; Lauque et al., 2023) |
| 11 | Physical space and ED layout | Limited or poorly designed space disrupts workflows and slows patient movement. | (Frohnweiler et al., 2024) |
| 12 | Health information technology and online systems | Inefficiencies in electronic medical records or clinical information systems delay documentation and access to information. | (Alhabib et al., 2024; Ansah et al., 2021) |
| 13 | Admission/discharge processes | Delays in discharge or transfer to inpatient wards lock bed availability and increase waiting times. | (Lauque et al., 2023; Panahi et al., 2022) |
| 14 | Hospital management policies and interdepartmental coordination | Poor decision-making and inadequate coordination between the ED and inpatient wards generate additional delays. | (Del Valle, 2020; Ansah et al., 2021) |

While the term optimization is often used in healthcare operations, this study adopts a policy-oriented improvement perspective rather than formal mathematical optimization. The focus is on evaluating alternative scenarios and identifying effective intervention strategies through simulation. From this perspective, the central research question of the present study is: How can the average patient waiting time in hospital emergency departments be reduced through a systemic understanding of input, throughput, and output factors, and through the design and evaluation of operational policies using a system dynamics approach? This research problem encompasses three components: identifying key variables based on domestic and international literature and semi-structured in-depth interviews with experts, developing a system dynamics model, and conducting policy experimentation.

Although simulation approaches such as discrete-event simulation (DES) and agent-based modeling (ABM) are widely used in healthcare systems, system dynamics was selected in this study for its ability to capture feedback structures, nonlinear interactions, and time delays at an aggregate level. DES primarily focuses on process-level operational detail and queue dynamics, while ABM emphasizes individual-level behaviors. In contrast, system dynamics enables the analysis of policy-level interventions and systemic feedback mechanisms, which aligns with the objective of this study to understand and improve overall system performance.

## 2. Research background

The literature indicates that prolonged emergency department length of stay is associated with numerous adverse outcomes. For example, a systematic review and meta-analysis demonstrated that a length of stay exceeding 24 hours among patients requiring intensive care is associated with increased mortality, although findings for shorter time intervals, such as four to eight hours, remain inconsistent. Nevertheless, extended stays among critically ill patients are associated with unfavorable clinical outcomes (Lauque et al., 2023). Other studies have shown that patient boarding after an admission decision is linked to higher mortality, prolonged mechanical ventilation, and increased length of stay in intensive care units (Mohr et al., 2020). In addition, large-scale operational studies suggest that higher numbers of boarded patients are directly correlated with slower admissions and greater delays (Greenwood-Ericksen et al., 2025). Beyond clinical consequences, prolonged emergency department stays also entail economic costs, including additional visits, repeated ED visits, and reduced resource efficiency (Sartini et al., 2022).

The research literature categorizes the determinants of patient length of stay in emergency departments into three main groups. Input factors include the rate of patient arrivals, the distribution of case severity, and temporal patterns of patient inflow. Unnecessary visits or self-referrals to emergency departments, often caused by limited access to primary care or the relative ease of ED accessibility, further increase input pressure (Sartini et al., 2022). Studies have also shown that seasonal factors, such as influenza outbreaks and an aging population, contribute to rising demand (Payne et al., 2023). Throughput factors consist of triage time, time to physician assessment, laboratory processing and reporting times, imaging procedures, the need for specialist consultations, and the efficiency of clinical decision-making. Research indicates that delays in imaging, such as CT scans, and prolonged laboratory turnaround times are among the most critical contributors to extended ED length of stay (Payne et al., 2023; Ayenew et al., 2024). Output factors include inpatient bed capacity, discharge or transfer times, and admission-related policies. Output bottlenecks occur when insufficient inpatient beds delay transfers, leaving patients in the emergency department for extended periods. This situation not only prolongs patient stays but also heavily consumes ED resources (Sartini et al., 2022; Greenwood-Ericksen et al., 2025).

At the practical level, various interventions have been identified, including establishing fast-track pathways for patients with lower acuity, increasing staffing levels during peak hours, improving laboratory turnaround times, using point-of-care testing, and enhancing interdepartmental coordination. Meta-analyses and empirical studies demonstrate that, when appropriately applied, such interventions can reduce patient length of stay. For instance, early warning systems and clearly defined care pathways, such as sepsis alerts, have been shown to accelerate clinical decision-making and reduce mortality (Kim et al., 2024).

System dynamics, through the use of causal loop diagrams and stock-and-flow models, can analyze phenomena characterized by feedback loops and delays, such as patient boarding, staff burnout, and reduced emergency department capacity. A review of the literature indicates that the application of system dynamics in hospital service studies has increased, with many focusing on optimizing patient flow (Mehrolhassani et al., 2025). In contrast to regression analysis, which is less capable of revealing time-dependent causal relationships, system dynamics can model the long-term effects of policies, unintended feedback, and unexpected consequences. It also facilitates stakeholder engagement and the development of more acceptable models.

Studies conducted in Iran have shown that contextual factors such as nurse shift scheduling, access to laboratory services, and interdepartmental admission processes play a significant role in prolonging patient length of stay in emergency departments. However, most of these studies have employed traditional methods or discrete-event simulation, and the application of system dynamics has been very limited (Mousavi Kashani and Zargar Balaye Jame, 2024; Abasi Niasar et al., 2024; Hosseini Firouzabadi and Hajian Heidari, 2022). The majority of previous research has analyzed determinants of length of stay in a static manner and has not addressed the modeling of complex interactions and delays. This lack of application of system dynamics within the specific context of Iran, given the unique characteristics of the referral system and hospital care resources, represents a significant research gap that the present study seeks to address. Table 2 summarizes previous domestic and international studies.

Table 2. Research background

| No. | Author(s) and Year | Research focus | Key findings |
|---|---|---|---|
| 1 | Ansah et al., 2021 | System dynamics modeling of ED crowding | Developed a "virtual ED" and showed that policies such as faster patient transfers and primary care services near the ED can reduce average length of stay. |
| 2 | Lauque et al., 2023 | Systematic review and meta-analysis on ED length of stay and inpatient mortality | Found that the length of stay longer than 24 hours among critically ill patients (e.g., ICU cases) is associated with higher mortality; findings for shorter intervals were inconsistent. |
| 3 | Sartini et al., 2022 | Narrative review of causes, consequences, and solutions for ED crowding | Identified both clinical and economic consequences of crowding, including reduced satisfaction, compromised quality of care, and higher costs; factors categorized as input, throughput, and output. |

| No. | Author(s) and Year | Research focus | Key findings |
|---|---|---|---|
| 4 | Mohr et al., 2020 | Effects of boarding critically ill patients in EDs on clinical outcomes | Confirmed that boarding is associated with prolonged mechanical ventilation, longer ICU stays, and increased mortality. |
| 5 | Greenwood-Ericksen et al., 2025 | Analysis of boarding, bed occupancy, and transfer decision-making | Found that increases in the number of boarded patients were directly associated with greater transfer delays and 6reduced inter-hospital admissions. |
| 6 | Payne et al., 2023 | Time-in-motion observational study of factors influencing ED length of stay | Demonstrated that imaging delays (e.g., CT scans) and paraclinical service delays (e.g., laboratory tests) are major contributors to prolonged length of stay. |
| 7 | Farimani et al., 2024 | Systematic review of models predicting ED length of stay | Reviewed a range of models, including machine learning and regression; however, limited consideration was given to complex interactions and feedback effects. |
| 8 | Ayenew et al., 2024 | Empirical study of factors linked to prolonged ED length of stay | Identified paraclinical delays and patient boarding as key determinants of longer stays. |
| 9 | Zhang et al., 2021 | System dynamics modeling for ED dynamic response | Developed a system dynamics model illustrating complex interactions and delays in ED operations, providing a tool for policy analysis. |
| 10 | Mousavi Kashani and Zargar Balaye Jame, 2024 | Predicting ED length of stay using machine learning | Applied machine learning models to predict length of stay, though interactions among factors and policy implications were not addressed. |
| 11 | Abasi Niasar et al., 2024 | Analysis of interdepartmental transfers of patients awaiting admission | Highlighted delays caused by poor interdepartmental coordination and admission processes; recommended more integrated procedures to reduce crowding. |
| 12 | Hosseini Firouzabadi and Hajian Heidari, 2022 | ED modeling using discrete-event simulation | Identified bottlenecks such as imaging and admission delays; no systemic approach was applied. |
| 13 | Badihi et al., 2021 | Effects of prolonged ED stays of critically ill patients on hospital outcomes | Reported that longer ED stays were associated with adverse clinical outcomes, extended hospital treatments, and increased costs. |

The review of international and domestic literature reveals that the factors contributing to increased average waiting time and patient length of stay in hospital emergency departments are numerous and recurrent, with clinically, economically, and organizationally significant consequences. System dynamics, as a comprehensive approach for analyzing and modeling complex systems with feedback loops, provides a suitable tool for identifying key intervention points and testing alternative policies. However, this approach has been underutilized within the specific context of Iranian hospitals. The present study seeks to address this gap by developing an evidence-based model, enriched through stakeholder participation, that has the potential to substantially reduce average patient waiting times.

## 3. Methodology

This study adopts a mixed methods system dynamics approach to analyze the factors influencing patient waiting time in hospital emergency departments and to develop policy-oriented solutions for performance improvement. The research integrates qualitative data collection and analysis with quantitative simulation modeling to provide a comprehensive understanding of system behavior.

The study was conducted in the emergency department of Kosar Hospital in Semnan, Iran, which functions as a major provincial referral center. The hospital is characterized by a high volume of patient inflow, including both urgent and non urgent cases, and operates continuously across triage, treatment, and discharge/transfer units. These characteristics make it an appropriate setting for examining patient flow dynamics and waiting time challenges.

The study utilized both qualitative and quantitative data sources. Qualitative data were collected through semi-structured interviews with key stakeholders, while quantitative data were obtained from hospital records covering a five-year period. These historical data were used for model calibration and to ensure that the simulation reflects real-world system behavior. The simulation time horizon was set to one year (8,760 hours) in order to capture seasonal variations and demand fluctuations.

The statistical population of the study consisted of key stakeholders associated with the hospital emergency department. Purposive sampling was employed to select participants with relevant knowledge and experience. A total of 12 experts participated in the interviews, including hospital executives, emergency department managers, physicians, nurses, and information technology specialists.

Participants were selected based on the following inclusion criteria:

- Direct involvement in emergency department operations
- Minimum of three years of professional experience
- Willingness to participate in the study

Exclusion criteria included:

- Lack of direct operational experience in the emergency department
- Incomplete or inconsistent interview responses

Data collection was carried out using multiple tools to ensure methodological rigor:

- Semi-structured interview protocols designed based on an extensive literature review
- Review of scientific articles and prior empirical studies
- Hospital administrative and operational datasets
- Vensim software (version 7.3.5) for system dynamics modeling and simulation

The research process was conducted in several sequential stages. First, a comprehensive review of the literature was performed to identify key variables affecting patient waiting time. Second, semi-structured interviews were conducted to capture context-specific factors and enrich the model structure. Third, qualitative data were analyzed using thematic analysis, through which codes, sub-themes, and main themes were identified.

Subsequently, causal loop diagrams were developed to represent feedback relationships among variables. Based on these diagrams, a stock-and-flow model was constructed, incorporating stock, flow, and auxiliary variables. Mathematical relationships among variables were then defined, and the model was implemented in the Vensim environment.

The developed model was simulated over a one-year time horizon using a time step of one hour. This configuration enabled the analysis of both short-term fluctuations and long-term system behavior. Different policy scenarios were designed and tested to evaluate their impact on patient waiting time and system performance.

The proposed policy scenarios were developed with consideration of real-world constraints, including staffing limitations, physical capacity, and interdepartmental coordination. The feasibility and practicality of these interventions were qualitatively assessed based on expert opinions to ensure their applicability in real healthcare settings.

To assess the validity of the model, extreme condition tests were conducted to evaluate system behavior under extreme input values. The results demonstrated that the model responds logically and consistently with real-world expectations. In addition, model outputs were compared with historical data to ensure behavioral realism.

This study has several limitations. First, the model is based on a single case study, which may limit the generalizability of the findings. Second, some parameters were estimated using expert judgment due to data constraints. Third, the model does not explicitly account for unexpected large-scale events such as disasters or pandemics. Despite these limitations, the study provides valuable insights into the dynamics of emergency department operations and policy interventions.

## 4. Findings

### *4.1. Interviews and thematic analysis*

In the first stage, by reviewing credible domestic and international research literature, the variables influencing patient waiting time were identified. To further enrich and complement the model, semi-structured interviews were conducted with 12 key stakeholders, including the hospital president, hospital management, information technology management, nursing management, emergency department management, the senior physician and head nurse of the emergency department, the triage physician, and three experienced nurses. These interviews aimed to identify influential variables that had received less attention in the literature and to gain a deeper understanding of the actual processes within emergency department operations.

The study's statistical population consisted of key stakeholders in the hospital's emergency department. For the collection of qualitative data, purposive sampling was employed.

The interview data were coded and categorized using a thematic analysis approach. The extracted codes were hierarchically organized into sub-themes, main themes, and core categories, as presented in Table 3. This analysis enabled the identification of actual causal relationships and critical points within the system, thereby enriching the model. The results of this analysis formed the basis for the design of the system dynamics model.

Table 3. Results of thematic analysis

| Sub-theme | Main theme | Core category |
|---|---|---|
| • Patient boarding in ED while awaiting admission<br>• Limited triage space<br>• Lack of separation between low-acuity and high-acuity patients | Insufficient physical capacity and beds | Hospital structure and capacity |
| • Shortage of physicians during peak shifts<br>• Nurse fatigue<br>• Suboptimal shift scheduling relative to patient inflow | Imbalanced distribution of human resources | |
| • Unclear pathways for trauma and non-trauma patients<br>• Repetition of tests due to weak communication with specialty wards | Inefficiency in patient flow | Clinical and managerial processes |
| • Lengthy admission processes for patients requiring hospitalization<br>• Poor coordination between ED and inpatient wards | Delays in admission and discharge decisions | |
| • Absence of common protocols for frequent cases<br>• Divergent physician opinions in patient prioritization | Lack of unified protocols | |
| • Slow registration of patient information<br>• Lack of real-time dashboard for bed status | Weaknesses in IT and HIS systems | Technology and information |
| • Absence of crowding alert systems<br>• Lack of patient inflow forecasting based on historical data | Insufficient performance monitoring tools | |
| • Seasonal peaks (influenza, road traffic trauma)<br>• Unforeseen events (mass accidents, natural disasters) | Unpredictable demand surges | External and environmental factors |
| • Patients with minor conditions visiting ED due to easier access<br>• Inability to redirect low-acuity patients to outpatient clinics | Burden of non-emergency visits | |
| • Conflicts between specialty physicians and ED staff regarding rapid admission<br>• Weak verbal communication within care teams | Insufficient interdepartmental collaboration | Organizational culture and workforce |
| • Impact of staff fatigue on decision-making speed<br>• Reduced motivation for innovation and process improvement | Psychological pressure and burnout | |

| Sub-theme | Main theme | Core category |
|---|---|---|
| • Absence of defined KPIs for waiting time<br>• Short-term reactions instead of sustainable policies | Lack of strategic crowding management plans | Policy and governance |
| • Inadequate referral pathways from primary care centers<br>• Concentration of non-urgent patient load on hospital EDs | Weak coordination with primary care networks | |

### 4.2. *System dynamics*

To analyze the behavior of a complex system over time, the system dynamics approach is essential. This approach emphasizes understanding the interactions among system variables through feedback loops, nonlinear effects, and time delays. Moreover, system dynamics enables the examination of the stock-and-flow nature of variables, thereby facilitating the analysis of overall system behavior over time. Owing to their quantitative orientation, system dynamics models can be simulated on computers and project the future state of the system based on a set of parameters and variables (Ataei et al., 2020).

Professor J. W. Forrester is recognized as the founder of the field of system dynamics. In his seminal book Industrial Dynamics, he demonstrated that by modeling the structure of human systems and their control policies, system behavior can be analyzed and predicted with accuracy (Faghfouri Azar et al., 2019). From John Sterman's perspective, system behavior is directly shaped by its structure. Accordingly, the dynamics hypothesis states that observed system behaviors arise from the structural interactions among its components and that structural changes can fundamentally alter the system's overall behavior (Sterman, 2002).

#### 4.2.1. *Problem definition and research horizon*

The increasing number of visits to emergency departments, coupled with limited inpatient bed capacity, human resources, and diagnostic and administrative processes, has resulted in long queues and rising average patient waiting times in hospitals. Among these, Kosar Hospital in Semnan, a provincial referral center, has faced multiple challenges in recent years that have affected patient waiting times in its emergency department. These challenges have not only reduced service delivery quality but also affected patient satisfaction and the efficiency of healthcare staff.

The research horizon of the present study was set to 1 year to fully account for seasonal fluctuations and common disease peaks, such as influenza during colder seasons and heat-related illnesses during warmer periods, and their effects on patient waiting times. For model calibration and simulation, real data from the past five years of the emergency department at

Kosar Hospital in Semnan were utilized. Accordingly, using the system dynamics approach, causal relationships among the key variables were identified and analyzed. The ultimate objective was to achieve a dynamic understanding of system behavior and to provide policy insights to reduce average waiting times and improve emergency department efficiency.

The system boundary of this study encompasses the emergency department's internal processes, including triage, treatment, and discharge/transfer. Endogenous variables include patient flow rates, workforce effectiveness, bed capacity, and waiting times. Exogenous variables include patient arrival rate, demand fluctuations, and the intensity of non urgent visits. This boundary definition ensures that the model captures the core internal dynamics while accounting for key external drivers.

### *4.2.2. Establishing causal relationships and designing the causal loop model*

By integrating the findings from the literature review and the interview analysis, a causal loop diagram of the emergency department was developed. This diagram illustrates all identified variables as reinforcing and balancing feedback loops and presents the complex interactions among them in a unified manner. The causal loop diagram of the emergency department system at Kosar Hospital in Semnan is presented in Figure 1.

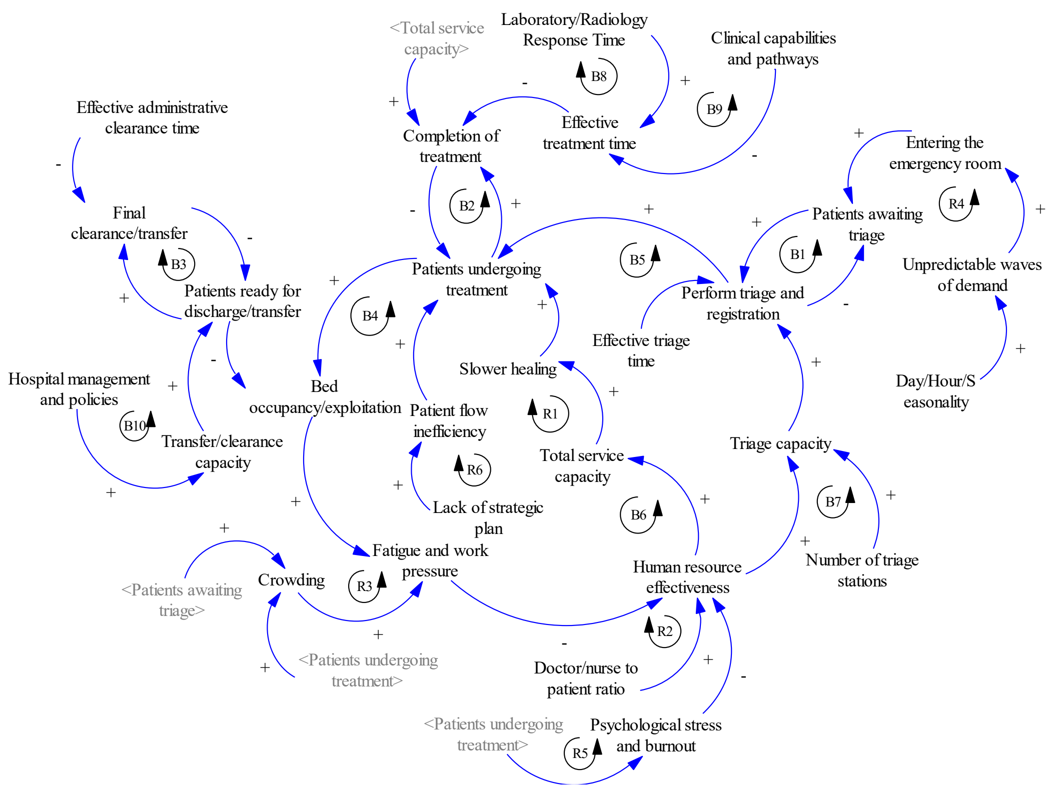



Figure 1. Causal loop model of the emergency department system

The causal loop structure of the model includes both reinforcing and balancing feedback mechanisms.

Reinforcing Loop (R1 – Congestion Loop): An increase in patient arrivals leads to higher emergency department crowding, which increases workload and staff fatigue. Increased fatigue reduces workforce effectiveness, leading to slower service rates and further accumulation of patients.

Balancing Loop (B1 – Capacity Adjustment Loop): Increasing staffing levels or improving workforce effectiveness enhances service capacity, which reduces waiting time and system congestion.

Balancing Loop (B2 – Discharge Flow Loop): Improved discharge and transfer processes increase outflow rates, reduce patient accumulation, and stabilize the system.

#### *4.2.3. Developing dynamic hypotheses*

The dynamic hypothesis is formulated to explicitly describe the feedback-driven structure underlying system behavior. It is based on the interaction between patient inflow, service capacity, and workforce dynamics.

At this stage, the behavior of variables and their interactions are defined in terms of dynamic hypotheses and inter-variable relationships. Accordingly, the dynamic hypothesis of the present study can be articulated as follows:

"When emergency department inflow (driven by baseline arrival rate, the intensity of non-urgent visits, and demand surges or fluctuations) exceeds triage and overall service capacity during certain periods, the number of patients under treatment and, consequently, bed occupancy and utilization increase. This escalation, by intensifying staff fatigue and workload, reduces workforce effectiveness. The decline in effectiveness simultaneously lowers triage capacity and overall service capacity, thereby slowing triage, registration, and treatment completion. Slower outflow enlarges both upstream and downstream queues, ultimately increasing the overall average waiting time. Conversely, improvements in the physician-to-nurse-to-patient ratio and streamlining transfer or discharge capacity create a reverse cycle, thereby reducing waiting times."

#### *4.2.4. Defining the role of variables and designing the stock-and-flow model*

Subsequently, the stock-and-flow model was developed based on the causal loop diagram. This model incorporates stock, flow, and auxiliary variables, enabling the simulation of managerial scenarios and the formulation of optimal policy interventions. Table 4 presents the variables and their respective roles in the model, while the final model is illustrated in Figure 2.

Table 4. Variables and their roles in the model

| No. | Type | Variable name |
|---|---|---|
| 1 | Stock | Triage |
| 2 | Stock | Treatment |
| 3 | Stock | Patients ready for discharge or transfer |
| 4 | Stock | Emergency department crowding |
| 5 | Flow | Entry to emergency department |
| 6 | Flow | Start of triage process |
| 7 | Flow | Completion of triage process |
| 8 | Flow | Start of treatment process |
| 9 | Flow | Completion of treatment process |
| 10 | Flow | Start of discharge or transfer process |
| 11 | Flow | Completion of discharge or transfer process |
| 12 | Auxiliary | Demand surge and fluctuation |
| 13 | Auxiliary | Intensity of non-urgent visits |
| 14 | Auxiliary | Baseline arrival rate |
| 15 | Auxiliary | Baseline triage time |
| 16 | Auxiliary | Case mix and disease severity |
| 17 | Auxiliary | Effective triage time |
| 18 | Auxiliary | Triage capacity |
| 19 | Auxiliary | Throughput per triage station |
| 20 | Auxiliary | Number of triage stations |
| 21 | Auxiliary | Effective treatment time |
| 22 | Auxiliary | Baseline treatment time |
| 23 | Auxiliary | Laboratory and radiology |
| 24 | Auxiliary | Overall service capacity |
| 25 | Auxiliary | Emergency department bed capacity |
| 26 | Auxiliary | Service rate per bed |
| 27 | Auxiliary | Workforce effectiveness |
| 28 | Auxiliary | Fatigue and workload |
| 29 | Auxiliary | Nurse-to-patient ratio |
| 30 | Auxiliary | Physician-to-patient ratio |
| 31 | Auxiliary | Discharge and transfer capacity |
| 32 | Auxiliary | Inpatient transfer capacity |
| 33 | Auxiliary | Share of outpatient discharges |
| 34 | Auxiliary | Effective discharge time |
| 35 | Auxiliary | Bureaucratic rate |
| 36 | Auxiliary | Baseline discharge time |
| 37 | Auxiliary | Waiting time for triage |
| 38 | Auxiliary | Waiting time for treatment |
| 39 | Auxiliary | Waiting time for discharge or transfer |
| 40 | Auxiliary | Average overall waiting time |

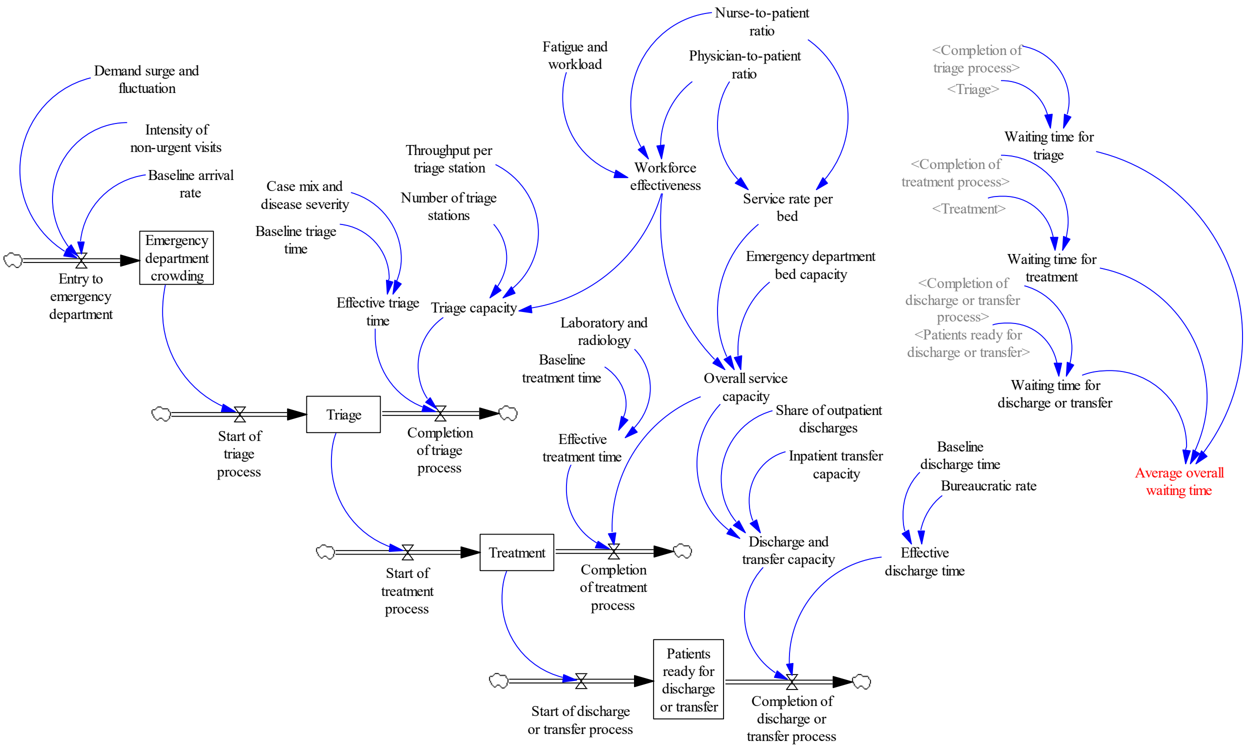


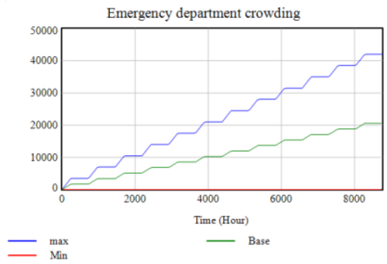

Figure 2. Stock-and-flow model of the emergency department system

### 4.2.5. Model simulation and validation

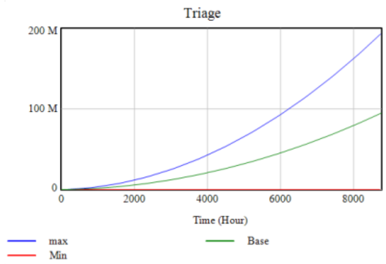
After defining the model structure and determining the relationships among the key variables of the emergency department system, the behavior of critical variables was simulated over a one-year time horizon. To ensure the accuracy and validity of the simulation results, an extreme condition test was conducted in Vensim. This test examines whether the model continues to exhibit logical and predictable behavior when inputs are pushed to extreme values (very high or very low). The results of these tests are presented in Figure 3.

For example, a complete reduction in patient arrival rate led to gradual stock depletion (ED crowding, triage, treatment, and discharge or transfer), resulting in a significant decrease in average waiting time. Conversely, doubling the patient arrival rate led to increases across all stocks and a marked rise in the average waiting time. These outcomes are consistent with the logic of the real-world system.

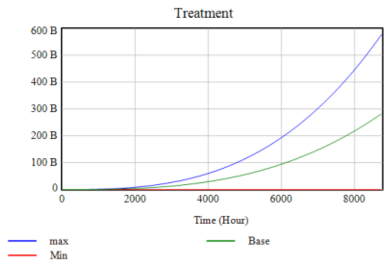
In addition to extreme condition tests, the model structure is grounded in established system dynamics principles, including feedback loops, stock-flow consistency, and behavioral plausibility. The model aims to capture the system's underlying structure and reproduce its general behavior patterns rather than exact numerical predictions.



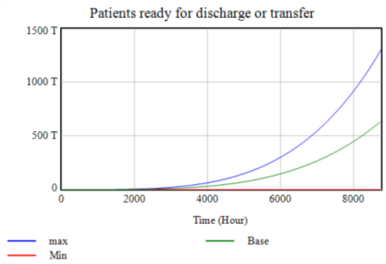

a: Emergency crowding



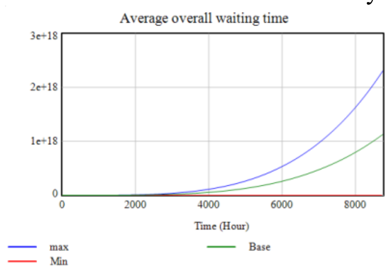

b: Triage




c: Treatment




d: Patient ready for discharge or taransfer




e: Avg overall waiting time

Figure 3. Results of the model extreme condition test

### *4.2.6. Model implementation and scenario development*

In this study, a one-year simulation horizon (8,760 hours) was considered to model patient flow behavior in the emergency department of Kosar Hospital in Semnan. This time frame allowed for the observation of patient arrival patterns, including seasonal fluctuations and non-urgent visits. The simulation was performed with a time step of 1 hour to examine both short- and long-term variations in patient queues and waiting times. The model consists of four main stocks representing the patient flow pathway within the emergency department:

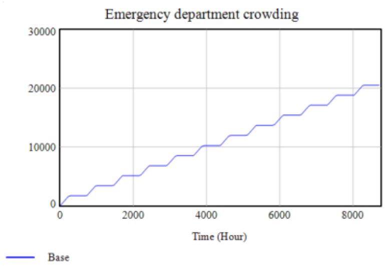
**Emergency department crowding:** Upon arrival, patients first enter this stock. The number of incoming patients is a function of the baseline arrival rate, the intensity of non-urgent visits, and demand fluctuation waves. This stock reflects the total number of patients present in the emergency department who have not yet entered the triage process.

**Triage:** After entering the ED, patients proceed to the flow, representing the start of the triage process. This stage includes the initial clinical assessment and determination of treatment priority. The number of patients triaged per time unit is determined by triage capacity and effective triage time.

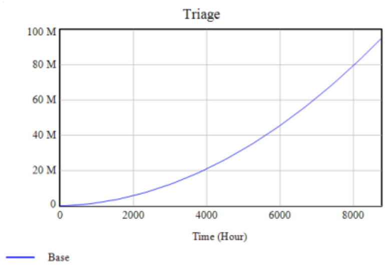
**Treatment:** After completing triage, patients move into the flow, representing the start of treatment. This stock represents patients currently receiving medical care. The overall service capacity and effective treatment time determine the number of patients who can be treated per hour.

**Discharge or transfer:** Upon completion of treatment, patients enter the flow representing the start of the discharge or transfer process. The number of patients discharged or transferred per time unit depends on the effective discharge time and the discharge/transfer capacity. This stage includes both outpatients discharged from the ED and inpatients transferred to other hospital wards.

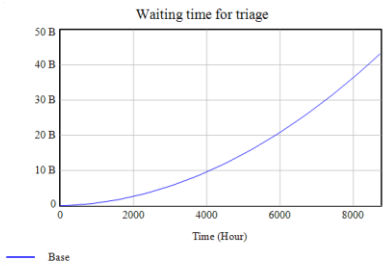
For each stage of the patient pathway, waiting time was calculated as the ratio of the stock size at that stage to the corresponding outflow rate. For example, the waiting time for triage was calculated by dividing the number of patients in triage by the number triaged per unit of time. Finally, the overall average waiting time across the entire patient pathway was calculated as the mean of the three waiting times, serving as the key performance indicator (KPI) for analyzing simulation results and evaluating policy scenarios. The results of the base-run simulation are presented in Figure 4.



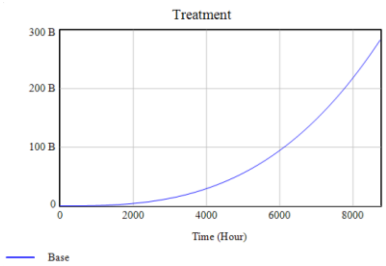

a: ED crowding



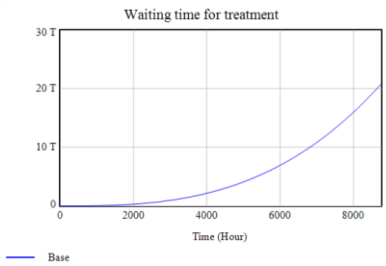

b: Triage



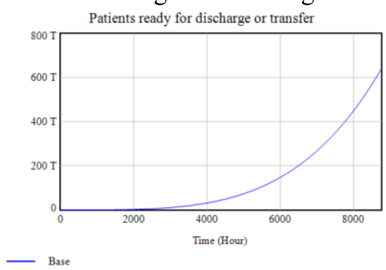

c: Waiting time for triage



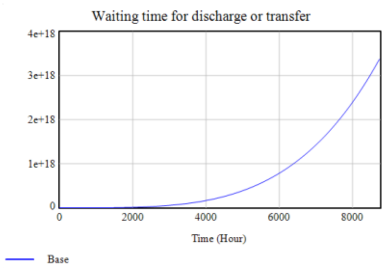

d: Treatment



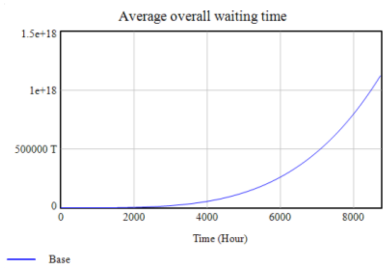

e: Waiting time for treatment




f: Patinet ready for discharge or transfer




g: Waiting time for discharge or transfer




h: AVG overall waiting time

Figure 4. *Base-run simulation results*

 DOI: 10.22067/JSTINP.2026.96638.1190

The results of the base-run simulation indicated that all stocks and waiting times increased throughout the simulation horizon. This behavior is logical and predictable, resulting from the combination of capacity constraints and the hospital's specific characteristics. Initially, emergency department crowding increases because the patient arrival rate is high, and Kosar Hospital, as the provincial referral center of Semnan, receives a large number of patients. This high inflow leads to patient accumulation in the initial emergency department queue.

In the triage stage, the increasing number of patients waiting causes both the triage stock and triage flow to rise. This is primarily due to the presence of only one triage station and a relatively long effective triage time, which limits patient processing capacity. Consequently, patient waiting time in triage also increases.

During the treatment stage, both patient accumulation and treatment flow follow an upward trajectory, driven by the limited overall service capacity. This limitation arises from shortages of physical resources such as beds, as well as low nurse-to-patient and physician-to-patient ratios. These constraints result in longer patient waiting times during the treatment phase.

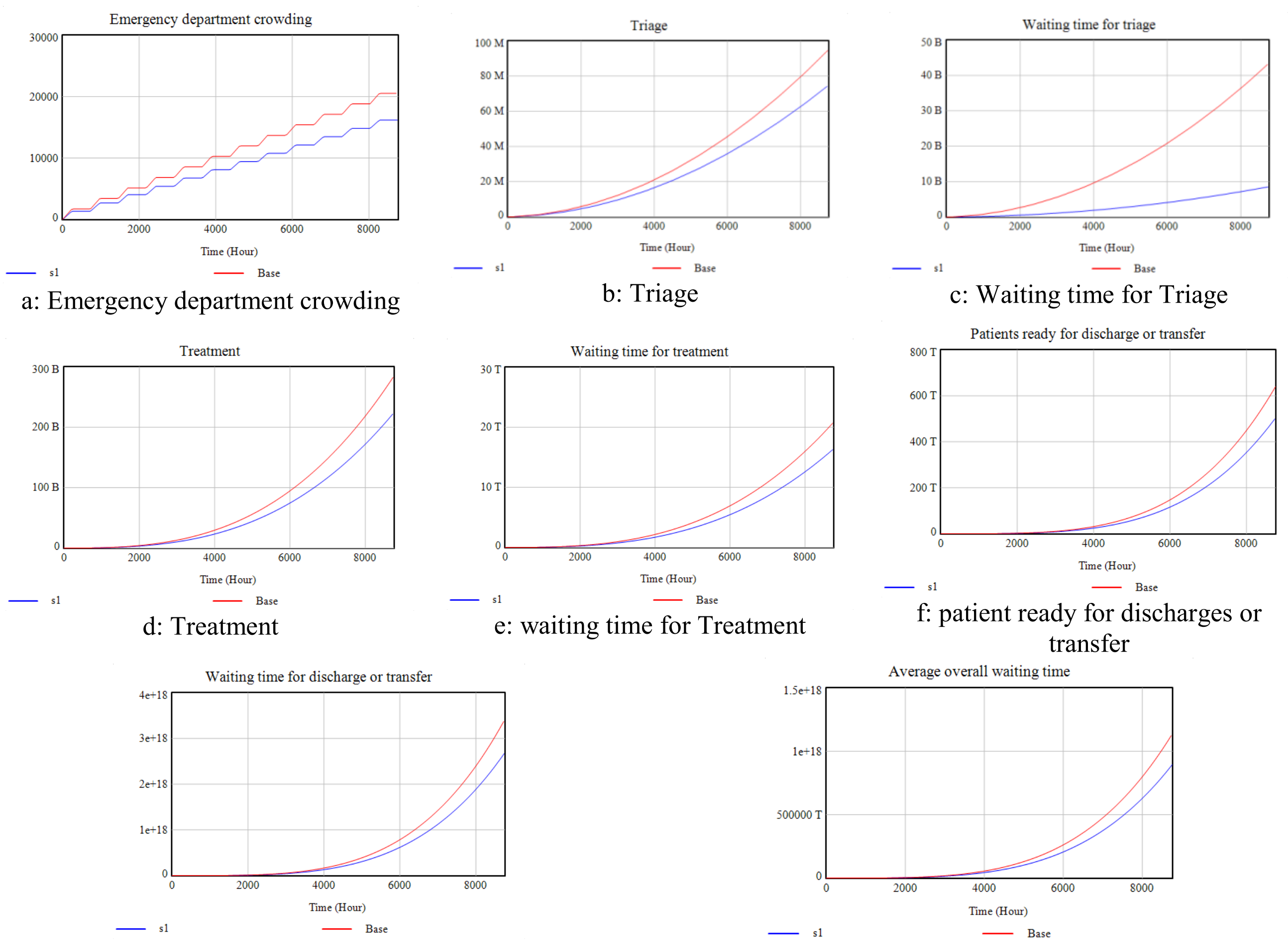
Finally, the discharge or transfer stock also shows an increasing trend, as the effective discharge time and discharge/transfer capacity are restricted. This leads to longer waiting times for patients at the discharge or transfer stage.

Overall, these combined factors cause the average total waiting time to increase progressively. In other words, capacity constraints, long effective times at each stage, and the high rate of patient arrivals collectively contribute to patient accumulation and prolonged overall waiting times.

After analyzing the model behavior under the base-run scenario and identifying the key bottlenecks and factors contributing to increased patient waiting times, a set of managerial and operational scenarios was designed to evaluate the effects of different policies and interventions on emergency department performance. The purpose of these scenarios was to examine the impact of changes in patient inflow, triage capacity, staffing levels, and discharge processes on patient queues and the overall average waiting time.

It should be noted that the numerical values of some model outputs may appear large due to the model's aggregate nature and the hourly simulation over a one-year horizon. Therefore, the model is primarily intended to analyze behavioral trends, relative changes, and policy impacts rather than absolute numerical predictions. to enhance interpretability, the focus is placed on comparative analysis across scenarios rather than absolute values.

**Scenario 1. Controlling the baseline patient arrival rate and increasing triage capacity:** Given that Kosar Hospital in Semnan serves as the provincial referral center, the volume of patient visits to the hospital is high. If, through coordination with other hospitals and healthcare centers in the city, patient visits to Kosar Hospital can be reduced by approximately 20%, the patient arrival rate will become more balanced, leading to decreased crowding across all stages. In addition, by increasing the emergency department's triage capacity to two triage stations and reducing the baseline triage time, initial-stage congestion can be mitigated, ultimately resulting in a lower overall average waiting time. The simulation results for this scenario are presented in Figure 5.




a: Emergency department crowding b: Triage c: Waiting time for Triage

d: Treatment e: waiting time for Treatment f: patient ready for discharges or transfer

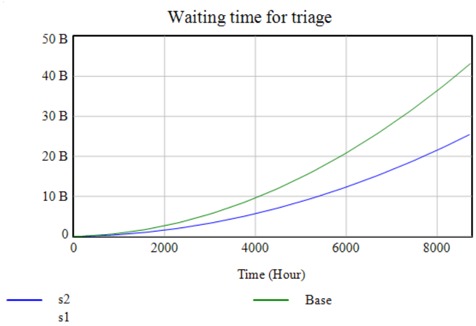
g: waiting time for discharge or transfer h: avg overall waiting time

Figure 5. *Simulation results for Scenario 1*

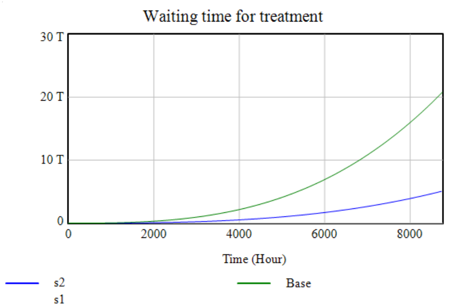
**Scenario 2. Improving workforce effectiveness by increasing the physician- and nurse-to-patient ratios:** By increasing the number of healthcare staff relative to patients, the overall effectiveness of the workforce improves, leading to enhanced service capacity in the emergency department and, consequently, reduced treatment waiting time and a lower overall average waiting time. In the base scenario, the nurse-to-patient ratio is 1:8, and the physician-to-patient

 DOI: 10.22067/JSTINP.2026.96638.1190

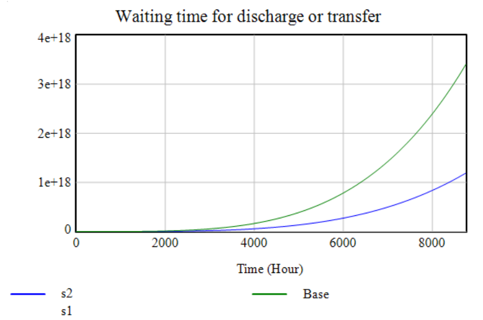
ratio is 1:4. If these ratios are improved to 1:6 for nurses and 1:3 for physicians, workforce effectiveness will increase, and with a higher service rate per bed, both treatment and discharge processes will be performed more efficiently and at a higher quality. These improvements collectively result in a noticeable reduction in both the average total waiting time and the waiting times across all stages of the process. The simulation results for Scenario 2 are illustrated in Figure 6.



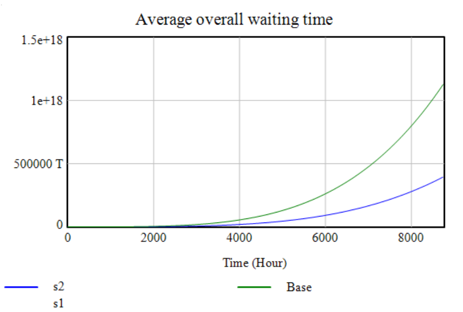

a: Waiting time for triage




b: Waiting time for treatment



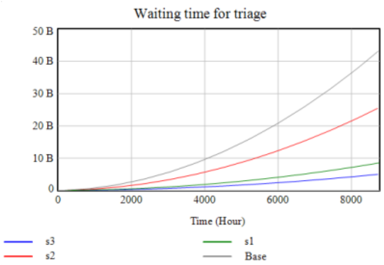

c: Waiting time for discharge or transfer



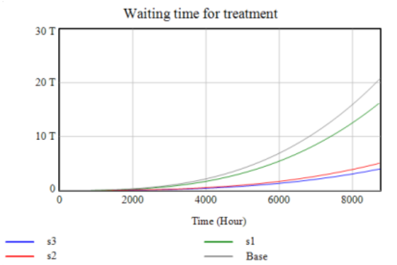

d: AVG overall waiting time

Figure 6. Simulation results for Scenario 2

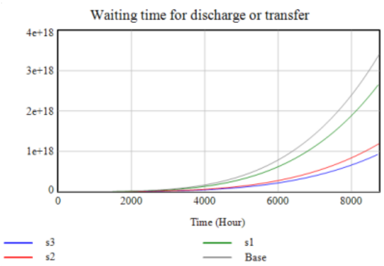
**Scenario 3. Combined scenario:** Simultaneous implementation of all interventions to assess synergistic effects and maximize system performance improvement :In this scenario, all improvement measures—including reducing the patient arrival rate, increasing triage capacity, and enhancing the physician-to-patient and nurse-to-patient ratios—are implemented simultaneously to evaluate the synergistic effects of these interventions on reducing waiting times and improving overall efficiency. The objective of this scenario is to assess the potential of concurrent policy implementation to achieve the greatest improvement in the overall performance of the emergency department system. The comparative impact of all interventions, highlighting the optimal results achieved in the combined scenario, is presented in Figure 7.



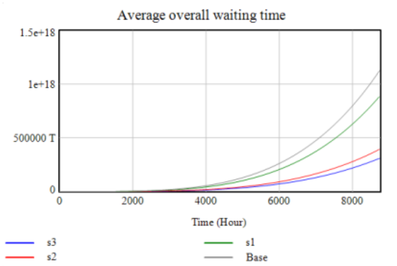
a: Waiting time for triage



b: Waiting time for treatment



c: Waiting time for discharge or transfer



d: AVG overall waiting time

Figure 7. Simulation results for Scenario 3

## 5. Discussion and conclusion

The results of this study should be interpreted within the context of a policy-oriented simulation model, where the primary objective is to understand system behavior and evaluate intervention strategies rather than to provide exact predictive outputs.

The developed simulation model of the emergency department at Kosar Hospital in Semnan enabled the examination of the effects of managerial policies and interventions on patient accumulation, waiting time at each stage, and the overall average waiting time. The base-run results revealed that due to the high patient arrival rate, limited triage capacity, shortages of equipment and human resources, and discharge process constraints, all stock levels and waiting times exhibited an upward trend, leading to a continuous increase in the overall average waiting time. The results obtained from the simulation of the three system dynamics scenarios provide a clear understanding of the impact of managerial and operational interventions on the performance of the emergency department at Kosar Hospital in Semnan.

In Scenario 1, controlling the baseline patient arrival rate through collaboration among hospitals across the city and reducing referrals to Kosar Hospital by 20% led to a noticeable decline in congestion during the initial stages of admission and reduced patient waiting times in the triage, treatment, and discharge stages. Furthermore, expanding triage capacity by adding an additional triage station and shortening the baseline triage time accelerated patient processing in the triage queue. Although this scenario showed a significant effect at the entry and triage stages, the persistence of capacity limitations in the treatment and discharge processes restricted its long-term impact on the overall average waiting time.

In Scenario 2, improving workforce effectiveness by increasing the physician-to-patient and nurse-to-patient ratios enhanced the system's efficiency, raised the service rate per bed, and expanded the total service capacity. These adjustments accelerated the triage, treatment, and discharge or transfer processes, resulting in a substantial reduction in waiting times across all stages and in the overall average waiting time. However, congestion in the ED entry phase and the limitations associated with the high patient inflow rate still remained.

In Scenario 3, the combined scenario that simultaneously implemented all improvement measures—reducing the arrival rate, increasing triage capacity, and enhancing staffing ratios—produced the most significant improvements. Under this scenario, all stages, including ED crowding, triage, treatment, and discharge, demonstrated considerable enhancement, and the overall average waiting time reached its minimum level. These findings highlight the synergistic effects of concurrent managerial and operational interventions, leading to more sustainable and efficient system performance.

Overall, the scenario analysis reveals that in the emergency department of Kosar Hospital, no single intervention alone can fully resolve the structural and procedural challenges. Instead, an integrated combination of managerial actions across input, process, and output levels can significantly enhance system efficiency. Therefore, the combined scenario was identified as the most effective strategy, as it substantially reduced the overall average waiting time, balanced patient inflow, treatment, and discharge processes, and ultimately improved both service quality and patient satisfaction.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## References

Abasi Niasar., A, Mahmoudi, H., Moradian, T. and Vafadar, Z., 2024. Evaluation of the Intra-Hospital Transfer Process for Critically Ill Patients in an Emergency Department of a University's Hospital in Tehran: A Cross Sectional Study.*Critical care nursing*, *17*(2), pp.76-84. URL: http://jccnursing.com/article-1-794-fa.html. [in Persian].

Alhabib, A., Almutairi, M. and Alqurashi, H., 2024. Patient-Centered care model's effectiveness in reducing patient waiting time in the emergency department: A systematic literature review. *Saudi Journal of Health Systems Research*, *4*(3), pp.103-113. https://doi.org/10.1159/000540398.

Ansah, J.P., Ahmad, S., Lee, L.H., Shen, Y., Ong, M.E.H., Matchar, D.B. and Schoenenberger, L., 2021. Modeling Emergency Department crowding: Restoring the balance between demand for and supply of emergency medicine. *Plos one*, *16*(1), p.e0244097. https://doi.org/10.1371/journal.pone.0244097.

Ataei, E., Sadeghian, R. and Najafi, P., 2020. Identification of factors affecting the burnout in the employees of ardabil regional water company and providing solutions using the system dynamics method. *Iranian Journal of Ergonomics*, *7*(4), pp.21-30. http://dx.doi.org/10.30699/jergon.7.4.21.

Ayenew, T., Gedfew, M., Fetene, M.G., Telayneh, A.T., Adane, F., Amlak, B.T., Workneh, B.S. and Messelu, M.A., 2024. Prolonged length of stay and associated factors among emergency department patients in Ethiopia: systematic review and meta-analysis. *BMC Emergency Medicine*, *24*(1), p.212. https://doi.org/10.1186/s12873-024-01131-6.

Badihi, E., Ghahremanzadeh Anigh, S., Janati, A., Ghaffarzad, A., Ebrahimi Bakhtavar, H. and Rahmani, F., 2021. Effect of Length of Stay in the Emergency Department on Hospital Outcome of Critically ill Patients: a Descriptive-Analytical Study. *Iranian Journal of Emergency medicine*, 8(1), p.8. https://doi.org/10.22037/ijem.v8i1.33259. [in Persian].

Davari, F., Nasr Isfahani, M., Atighechian, A. and Ghobadian, E., 2024. Optimizing emergency department efficiency: a comparative analysis of process mining and simulation models to mitigate overcrowding and waiting times. *BMC medical informatics and decision making*, *24*(1), p.295. https://doi.org/10.1186/s12911-024-02704-y.

Del Valle, A.R., 2020. *Implementation and Sustainability of Emergency Department Wait Time Management Strategies*. Walden University. Available at: https://scholarworks.waldenu.edu/dissertations/9236/.

Faghfouri Azar, A., Bakouie, F., Mahdavi Adeli, M.H., Radfar, R. and Afshar Kazemi, M.A., 2019. Designing a dynamic model to analyze social capital with system dynamics approach. *Social capital management*, *6*(4), pp.445-473. https://doi.org/10.22059/jscm.2019.282916.1866. [in Persian].

Farimani, R.M., Karim, H., Atashi, A., Tohidinezhad, F., Bahaadini, K., Abu-Hanna, A. and Eslami, S., 2024. Models to predict length of stay in the emergency department: a systematic literature review and appraisal. *BMC Emergency Medicine*, *24*(1), p.54. https://doi.org/10.1186/s12873-024-00965-4.

Frohnweiler, S., Heesemann, E., Perez-Alvarez, M., Santos Silva, M. and Vollmer, S., 2024. Hospital construction and emergency waiting time: evidence from Nicaragua. *Journal of Development Effectiveness*, *17*(2), pp.161-177. https://doi.org/10.1080/19439342.2024.2414029.

Greenwood-Ericksen, M., Kamdar, N., Swenson, K., Pruitt, P., McCrum, M.L., Paul, G., Myaskovsky, L., Kocher, K.E. and Zachrison, K.S., 2025. Emergency department boarding, inpatient census, and interhospital transfer acceptances. *JAMA Network Open*, *8*(5), p.e2512299. https://doi.org/10.1001/jamanetworkopen.2025.12299.

Hosseini Firouzabadi, S.M. and Hajian Heidari, M., 2022. Modeling and Improving a Hospital Emergency Department Using Discrete Event Simulation. *Second International Conference on Optimization of Production and Service Systems*, Rudsar. Available at: https://civilica.com/doc/1568159. [in Persian].

Kim, H.J., Ko, R.E., Lim, S.Y., Park, S., Suh, G.Y. and Lee, Y.J., 2024. Sepsis alert systems, mortality, and adherence in emergency departments: a systematic review and meta-analysis. *JAMA network open*, *7*(7), p.e2422823. https://doi.org/10.1001/jamanetworkopen.2024.22823.

Lauque, D., Khalemsky, A., Boudi, Z., Östlundh, L., Xu, C., Alsabri, M., Onyeji, C., Cellini, J., Intas, G., Soni, K.D. and Junhasavasdikul, D., 2022. Length-of-stay in the emergency department and in-hospital mortality: a systematic review and meta-analysis. *Journal of clinical medicine*, *12*(1), p.32. https://doi.org/10.3390/jcm12010032.

Mehrolhassani, M.H., Goudarzi, R. and Akhondzardaini, R., 2025. Applications, Key Variables, and Implementation Challenges of System Dynamics in Hospital Performance: A Scoping Review. https://doi.org/10.5812/jnms-161567.

Mohr, N.M., Wessman, B.T., Bassin, B., Elie-Turenne, M.C., Ellender, T., Emlet, L.L., Ginsberg, Z., Gunnerson, K., Jones, K.M., Kram, B. and Marcolini, E., 2020. Boarding of critically ill patients in the emergency department. *JACEP Open*, *1*(4), pp.423-431. https://doi.org/10.1002/emp2.12107.

Mousavi Kashani, S. and Zargar Balaye Jame, S., 2024. Predicting the Length of Stay of Patients in the Emergency Department of the Hospital using Machine Learning Models. *Military Caring Sciences (MCS)*, *11*(2), pp.114-123. http://dx.doi.org/10.22034/11.2.114. [in Persian].

Panahi, M., Ahmadnezhad, S., Farzaneh, R., Talebi Doluee, M., Akhavan, R. and Abbasi, B., 2022. Systematic Review of the Training Needs of Emergency Professional . *Journal of Practical Emergency Medicine*, *9*(1), e15. https://doi.org/10.22037/ijem.v9i1.38512. [in Persian].

Payne, K., Risi, D., O'Hare, A., Binks, S. and Curtis, K., 2023. Factors that contribute to patient length of stay in the emergency department: A time in motion observational study. *Australasian Emergency Care*, *26*(4), pp.321-325. https://doi.org/10.1016/j.auec.2023.04.002.

Sartini, M., Carbone, A., Demartini, A., Giribone, L., Oliva, M., Spagnolo, A.M., Cremonesi, P., Canale, F. and Cristina, M.L., 2022, August. Overcrowding in emergency department: causes, consequences, and solutions—a narrative review. In *Healthcare* (Vol. 10, No. 9, p. 1625). MDPI. https://doi.org/10.3390/healthcare10091625.

Siddiqui, F.J., Kumar, A., Ansah, J.P., Yuan, G., Liu, Z., Malhotra, R., Ong, M.E.H. and Lam, S.S.W., 2025. Long-range forecasting for emergency care systems in a highly dynamic setting: a Singapore case study. *JACEP Open*, *6*(4), p.100184. https://doi.org/10.1016/j.acepjo.2025.100184.

Sterman, J.D., 2002. System Dynamics: systems thinking and modeling for a complex world. Massachusetts Institute of Technology. http://hdl.handle.net/1721.1/102741.

Wang, H., Sambamoorthi, N., Robinson, R.D., Knowles, H., Kirby, J.J., Ho, A.F., Takami, T. and Sambamoorthi, U., 2024. What explains differences in average wait time in the emergency department among different racial and ethnic populations: A linear decomposition approach. *JACEP Open*, *5*(5), p.e13293. https://doi.org/10.1002/emp2.13293.

Zhang, G.S., Shen, X.Y., Hua, J., Zhao, J.W. and Liu, H.X., 2021. System dynamics modelling for dynamic emergency response to accidents involving transport of dangerous goods by road. *Journal of advanced transportation*, *2021*(1), p.2474784. https://doi.org/10.1155/2021/2474784.