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Factors impacting patient flows in the emergency department

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Abstract

Purpose – Emergency departments (EDs) are essential to hospital operations, involving complex processes and interactions with several hospital departments. As the entry point for many patients, EDs often face challenges such as overcrowding, staffing shortages and disruptions to patient flow, all of which negatively impact patient satisfaction. This paper aims to use discrete-event simulation and lean healthcare to analyse patient flows, exploring multiple scenarios to improve both patient experience and operations management.

Design/methodology/approach – Researchers combined Lean principles with discrete-event simulation to model the entire patient flow through the ED and its interactions with other hospital departments. Various scenarios were simulated to explore potential improvements in resource allocation, inpatient admissions and reductions in non-urgent cases.

Findings – This study demonstrates that reducing wait times for inpatient admissions significantly decreases all ED patients' average length of stay (ALOS). Furthermore, reducing the number of non-

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urgent patient admissions has a substantial impact on ED metrics, as these patients represent over 40% of admissions and consume significant resources. Overall, combining all improvements led to a reduction in ALOS by more than 30%.

Originality/value – This paper uses simulation to characterise ED operations and assess the influence of other hospital departments on patient flow. This approach provides a quantitative understanding of the role these departments play in ED overcrowding. In addition, this study compares different patient workflow characteristics and their effects, highlighting the importance of workflow decisions in shaping patient experiences.

Keywords Lean healthcare, Emergency department, Operations management, Discrete-event simulation, Business process management

Paper type Research paper

1. Introduction

Emergency departments (ED) are among the most complex areas of healthcare services, serving as the entry point for many patients (von Eiff and von Eiff, 2016). Several factors impact its overcrowding, including arrival times, process flows and outputs (Lindner and Woitok, 2021; Morley *et al.*, 2018; Savioli *et al.*, 2022). In the model by Lima *et al.* (2024), the authors discuss the end-to-end patient journey in the ED, presenting outcomes and decision-making processes that influence the flowcharts and highlighting the existing complexity. In this context, scientific publications have focused on this department, adapting various approaches and technologies to enhance efficiency and improve the quality of the services provided (Lima *et al.*, 2021; Santos *et al.*, 2023).

Lean healthcare (LH) is one of the most utilised approaches in hospital operations, focusing its efforts on waste reduction and increasing value for the patient (Lima *et al.*, 2021). The rise in academic publications in the field reinforces the obtained results, mainly focused on patient flows and reduction of waiting times (Lima *et al.*, 2021; Santos *et al.*, 2023). Additionally, LH stands out for its flexibility in combining with other approaches and technologies, such as project management, Six Sigma and event simulation (Crema and Verbano, 2019; Lopes *et al.*, 2023). The use of lean aligns with the concepts of value-based healthcare, having a positive impact on the patient experience (Barnabè *et al.*, 2019).

Concurrently, the use of technologies in healthcare operations is increasing and has a significant impact on the quality of the service (Wahyuni *et al.*, 2024). Data analytics, event simulation, and Industry 4.0 technologies have proven to be of great value for better hospital management (Galetsi and Katsaliaki, 2020; Vázquez-Serrano *et al.*, 2021; Zhong *et al.*, 2022). Among these, the construction of simulation models plays an important role by allowing the development of hypothetical scenarios and the prediction of outcomes, anticipating errors and unnecessary expenses (Castanheira-Pinto *et al.*, 2021). Moreover, it is possible to estimate the impacts on the system and outcome indicators before implementing a transformation, thereby avoiding potential declines in service quality (Castanheira-Pinto *et al.*, 2021).

Given this context, the present article aims to develop a detailed study of the patient flows in the ED of a large hospital. This is done by modelling the flow, followed by a comprehensive data analysis, complemented by discrete-event simulation (DES). Finally, proposals were studied for confirmation of the capacity installed or development of improvements to the process, as well as studying the impact of other hospital areas on ED operations.

2. Background

2.1 Hospital operations management

Health operations management is a complex field that faces challenges such as improving efficiency, constant changes and resource management (Figueroa *et al.*, 2019). In the case of private hospitals, additional aspects such as financing and payment difficulties, workforce retention, regulation and public trust in the service may also exist (Zhang *et al.*, 2024). In this context, various projects have been implemented to achieve better outcomes, often combining methods and tools from other sectors (Lopes *et al.*, 2023). There are numerous opportunities throughout the hospital where technology serves as an enabler to enhance outcomes. However, its implementation faces challenges, including a lack of process automation, inconsistent information and disconnected databases (Souza *et al.*, 2025).

In this context, technological advancements such as 5G can enable the adoption of new technologies, enabling real-time data analysis, telemedicine and artificial intelligence (AI), for example. Their use aligns with the concept of "smart hospitals," improving both patient care and facility management (Elendu *et al.*, 2024). Combining these different Industry 4.0 technologies to develop digital twins can improve hospital operations; however, there are ethical, social and technological barriers that must be carefully considered (Armeni *et al.*, 2022).

Characterised by the inherent complexity (Lima *et al.*, 2024), EDs have been studied with the adoption of new technologies. AI has been increasingly adopted mainly to support decision-making in activities like triage (Boonstra and Laven, 2022; Piliuk and Tomforde, 2023). However, although there are benefits, barriers such as model interpretation, privacy and biases exist, making it necessary to conduct more studies integrating AI into clinical workflows to increase its adoption (Cheng *et al.*, 2024). This integration can be achieved by combining it with other approaches like DES (Ortiz-Barrios *et al.*, 2024) and telemedicine (Soltane *et al.*, 2024), bringing benefits for both patients and operations.

2.2 Lean healthcare

Among the approaches used in hospital operations, Lean Healthcare stands out, with an increasing number of publications in recent years (Santos *et al.*, 2023). The results obtained include patient safety and satisfaction, increased efficiency and reduced waiting times (Dobrzykowski *et al.*, 2016; Ferreira *et al.*, 2018; Lima *et al.*, 2021), with evidence of improvements also in the healthcare supply chain (Alemsan *et al.*, 2022). However, there are implementation barriers that hinder the use of this approach, typically related to leadership (Santos *et al.*, 2023), human resources (Leite *et al.*, 2024; Lindsay and Aitken, 2024) and the choice of the problem, goal clarity and team autonomy (Danese *et al.*, 2024).

Waste and value are two main concepts adopted by Lean in healthcare (Graban, 2016). Some examples are unnecessary exams, poor layout and waiting times, but all lean wastes can be identified in a hospital (Graban, 2016). To identify and reduce those, various tools are applied, such as Value-Stream Mapping (VSM), process modelling, 5S and Gemba walking (de Barros *et al.*, 2021; Lima *et al.*, 2021; Santos *et al.*, 2023; Sordan *et al.*, 2023).

Although there are applications in other hospital areas (Souza *et al.*, 2022), the ED is the most studied area in the literature (Lima *et al.*, 2021; Santos *et al.*, 2023). The ED presents several opportunities for improvement, such as reducing waiting times and optimising flows (Sordan *et al.*, 2023; Tiso *et al.*, 2021), and it plays a fundamental role in the hospital's operation as it is the entry point for many patients into the service (Lima *et al.*, 2024). Furthermore, ED overcrowding is a recurring problem in the literature, caused by both internal and external factors (Joseph and White, 2020; Lindner and Woitok, 2021; Savioli *et al.*, 2022), highlighting the ED's relationship with other hospital areas. In this sense, improving patient flow, design, and process optimisation are strategies that can improve the situation (Joseph and White, 2020; Lindner and Woitok, 2021; Al Owad *et al.*, 2022), along with human resources allocation (Van Der Linden *et al.*, 2019). With the application of Lean Healthcare, overcrowding can be reduced, aligned with a positive impact on indicators such as length of stay (LOS), waiting times and patient satisfaction (Buestan *et al.*, 2024; Chaves *et al.*, 2023; Improta *et al.*, 2018; Tiso *et al.*, 2021).

2.3 Discrete-event simulation

Given the various challenges in the healthcare sector, changes have been made in recent years. Some authors adopt the term Health 4.0, which includes the use of technologies, patient-centred service, big data analytics (BDA) and new business models as facilitators for its implementation (Sony *et al.*, 2023). In this context, there has been an increase in the number of studies relating to BDA in healthcare, applying various techniques such as modelling, machine learning and simulation (Galetsi and Katsaliaki, 2020). In addition, LH and *H4*.0 can be combined, improving the results of its application (Tortorella *et al.*, 2023).

Simulation is used in various hospital areas, often combined with other techniques such as Lean Six Sigma (Vázquez-Serrano *et al.*, 2021). It allows for creating and evaluating improvement scenarios without the need for actual implementation, enabling the prediction of results, benefits and difficulties (Castanheira-Pinto *et al.*, 2021). Some factors that influence a reliable model include the engagement of stakeholders, its utility and feasibility (Vázquez-Serrano *et al.*, 2021). The barriers encountered often relate to the professionals' culture and resistance to change, with a low number of implementation examples in studies (Günal and Pidd, 2010; Vázquez-Serrano *et al.*, 2021). In addition, models can be less reusable, focused on specific contexts, and not consider other hospital areas beyond the modelled one (Günal and Pidd, 2010). Obtaining complete and reliable data can also be problematic, as they are essential for a good characterisation of the service reality (Guo *et al.*, 2016).

Nonetheless, many studies report positive results related to efficiency, patient safety and service quality, with the ED being one of the most studied areas (Chen *et al.*, 2020; Crema and Verbano, 2019; Vázquez-Serrano *et al.*, 2021). The possibilities for using simulations in the ED are numerous, with examples addressing various existing problems. Castanheira-Pinto *et al.* (2021) developed a model that shows the impact of reallocating physical resources on waiting times, considering factors such as entry rates and different treatments. Other studies have combined VSM and simulation to explore different layouts, allowing for better resource allocation (Wang *et al.*, 2015). The complexity of the ED becomes clear in models that explore its relationship with other departments, with patient transport being one of the bottlenecks that simulations can identify (Zhao *et al.*, 2015). In this context, models have been used to seek better dispatch rules, combined with real-time location technologies, to reduce the time spent on these activities (Huang *et al.*, 2024a; Huang *et al.*, 2024b). Finally, Demir *et al.*'s (2024) model considers the operation of the entire hospital, including the ED, outpatient and inpatient areas, aiming to reduce health disparities. This holistic approach allows for understanding and simulating decision-making scenarios that consider the relationships between hospital areas (Demir *et al.*, 2024).

3. Methodology

This article presents a case study conducted in the ED of a large public hospital located in northern Portugal. Case study is a scientific method that allows the exploration of complex issues in their real settings (Crowe *et al.*, 2011), contributing to the cumulative development of knowledge (Flyvbjerg, 2006) and useful for exploring aspects related to healthcare delivery (Crowe *et al.*, 2011). Moreover, this case can be considered a typical case that can represent the ED environment and give insights about its behaviour (Seawnght and Gerring, 2008).

The hospital divides the emergency department into paediatric, gynaecology and obstetrics, and adult emergency sections. This research focuses solely on the adult emergency section, which includes medical professionals specialized in general practice

(GP), surgery, orthopaedics, and internal medicine. Other specialists can be called from specific departments as the ED is attached to the main hospital building.

For the development of this research, initial meetings were held with the ED team, and the patient flow was manually mapped using Gemba Walking. This allowed the identification of wastes, bottlenecks, and main resources within the ED, which was followed by analysis activities focused on the main type of adding value activities in the patient flow. Subsequently, the hospital provided anonymized data for a one-year period, which was used to validate and detail the modelled process. After cleaning the database, the total number of cases used to characterize the study was 82,695. Following this, a simulation model was developed and validated using Simio® software. Finally, the researchers created hypothetical scenarios to explore the relationships between flow activities, stakeholders and the impact of improvements. These scenarios were selected based on the information collected during the initial steps of the project, following the objective of improving value-added activities in the patient flows. Each scenario was simulated over a one-year period, with several iterations. Table 1 summarizes the steps used. The research was approved by the ethics committees of both the researchers' educational institution (process reference code: CEICVS 063/2023) and the studied hospital (process reference code: 47/2023).

4. Results

This section presents the paper's results, showcasing insights from each methodological step. It is divided sequentially, following the model development phases presented in the previous section.

4.1 Case description

By analysing the patient flow in the ED and modelling the process, it is possible to conceptually simplify it into five elements: patient arrival, admission, triage, diagnosis and treatment, and discharge. Each of these stages can be detailed according to the study's objectives. For example, arrivals can be differentiated between walk-ins and ambulances, triage can define priorities impacting the flow, and discharges can be transferred to other institutions, hospital departments or discharged to home (Lima *et al.*, 2024). However, a broader initial view, as presented in Figure 1 and similar to representations by other authors (Castanheira-Pinto *et al.*, 2021; Demir *et al.*, 2024), already allows for a minimal understanding of the necessary data to characterize the flow and enables the identification and calculation of metrics of interest, such as the waiting time between triage and medical care, and the total LOS.

Another factor that can impact patient flows is the physical movement within the hospital, which depends on the hospital layout. In the studied case, the ED has seven main rooms: admission, triage, emergency room, non-urgent and urgent priorities (2 rooms), very urgent priorities (internal medicine and general surgery/orthopaedics - a shared room between these

Table 1. Methodological approach

Step	Name	Description
1	Current situation analysis	Use of lean techniques and tools to characterize the patient flow
2	Data analysis	Deepening the understanding of hospital data and adjusting the modelled process
3	Model development	Development and validation of the model, making necessary adjustments to the software
4	Patients' flow analysis	Simulation of hypothetical scenarios to explore relationships and propose improvements guided by lean healthcare

Source(s): Authors' own work

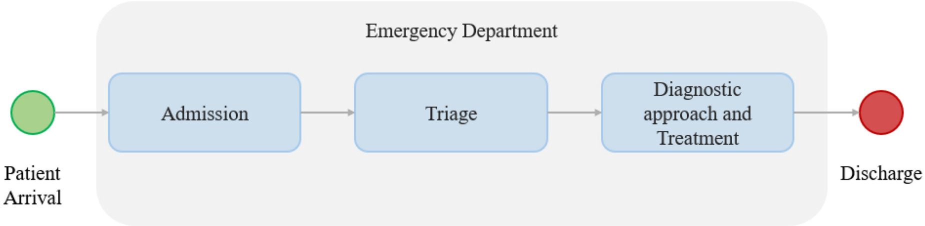

Figure 1. Simplified patient workflow
Source(s): Authors' own work

two surgical specialties). In a typical event, the patient enters through the access door and moves sequentially through the admission, triage, and diagnosis/treatment areas, depending on his/her clinical priority and the required medical specialty. Each of these rooms has specific waiting areas for patients. Additionally, patients might need to move to other areas for complementary exams or to see a specialist not present in the ED. These movements, besides affecting the time a patient spends in the service, can require human resources, especially for patients with reduced mobility, where an Operation Assistant is needed to help the transport. For emergent patients, usually arriving by ambulance, the admission and triage procedures are bypassed, and the patient goes directly to the emergency room.

During the patient's journey, decisions are made that influence their flow, such as referrals to specialties (either internal or external to the ED), performing complementary exams, and re-triage, leading to various possible flows. Moreover, several resources are part of the service, including physical and human factors. For this project, only the most demanded human resource of each room was considered, once they are normally the bottleneck of the service, as detailed in Table 2. The quantitative description of the patient sample will be detailed in the following sections.

4.2 Data analysis

This section characterizes the ED episodes based on the given database, defining the main stages of the patient flow. In addition, the data is compared to the initial understanding, presenting necessary adjustments according to the available data.

Table 2. Considered resources

Room	Physical resources	Human resources
Admission	18 chairs	2 operational assistants
Triage	3 offices	2 nurses
Diagnostic/treatment – Non-Urgent priority	20 chairs, 13 recliners, 2 medical offices	7 doctors (day), 5 doctors (night) – shared with GP Room 2
Diagnostic/treatment – urgent priority	14 stretchers, 2 medical offices, 1 electrocardiogram office	7 doctors (day), 5 doctors (night) – shared with GP Room 1
Diagnostic/treatment – very urgent priority (internal medicine)	10 recliners, 4 stretchers, 3 medical offices	4 doctors
Diagnostic/treatment – very urgent priority (surgery/orthopaedics)	14 chairs, 6 recliners, 6 stretchers, 3 medical offices, 1 minor surgery room	3 orthopaedists and 4 surgeons
Emergency room (red room) – dedicated to critical patients	5 emergency bays (including Trauma)	2 doctors

Source(s): Authors' own work

4.2.1 Patients arrival. Patient arrivals at the ED are variable due to the spontaneous nature of these events, challenging service planning and potentially causing an imbalance between service capacity and patient needs. Therefore, the decision was made to characterize patient entry rates by hour and day of the week to represent these variations. Figure 2 represents this analysis, grouped by weekdays and weekends.

From the figure, it can be observed that there are more admissions during weekdays. Monday has the highest number of admissions, while Sunday has the lowest. Overall, the early weekdays have a higher admission rate compared to the weekends. Additionally, there is an increase in admissions in the late morning and early afternoon, with significantly fewer admissions during the night. This pattern is consistent across all days of the week when analysed individually.

4.2.2 Admission. As previously mentioned, admission involves completing documents and administrative information at a service desk, supported by operational assistants. In the provided data, there is only one recorded time, which is logged when the assistant saves the information. Therefore, to estimate the duration of this activity, a uniform distribution with a minimum of 3 and a maximum of 5 min was considered, and the values were validated with the ED professionals.

Another aspect that the provided data allowed us to identify were the hyper-users, defined by the studied hospital as patients who visit the ED four or more times in a year. In total, 4.57% of the patients fell into this category, accounting for 16.40% of the visits during the studied period.

4.2.3 Triage. After admission, patients wait for triage, which is conducted by nurses according to the Manchester protocol. The hospital system records both the start and end times of this activity, allowing for the calculation of its duration. From the sample, the maximum likelihood method was used to identify a distribution that best represented the duration. A Lognormal distribution with location and scale parameters of 0.8504 and 0.7745, respectively, was obtained, with the result in minutes, as shown in Figure 3.

The adopted triage protocol assigns patients a priority scale by colour, which sets time targets for medical care and flowcharts according to the patients' clinical report. This information, as well as the destination room, was provided by the hospital and is crucial for determining the patient's flow.

During the studied period, the quantities of each "colour" assigned to patients were analysed, revealing a predominance of patients with yellow, green and orange wristbands, respectively. Due to this, and the clinical similarity of non-urgent cases, blue wristband patients were grouped with the green ones. Patients with red wristbands, as mentioned earlier, follow an independent flow, bypassing admission and triage activities and having exclusive medical and room resources. Therefore, they were excluded from this study, given

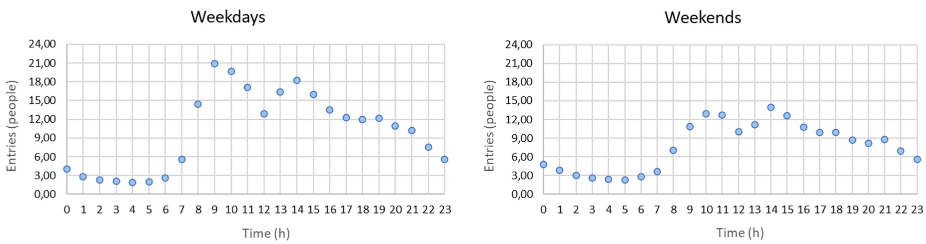

Figure 2. Patients arrival rates
Source(s): Authors' own work

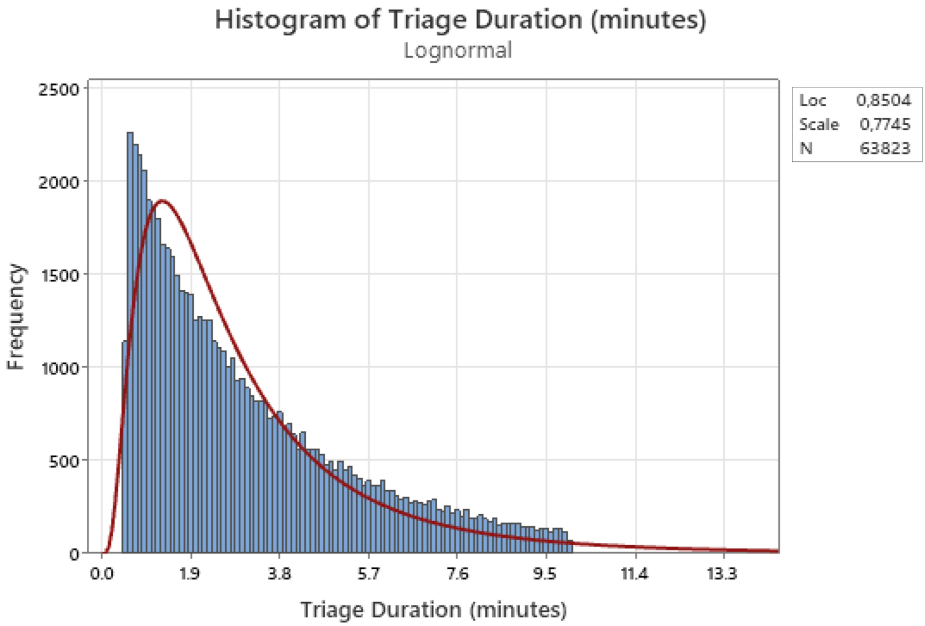

Figure 3. Triage data fitting
Source(s): Authors' own work

that they always receive priority, have very specific characteristics, and the volume of data for these cases was too small, making quantitative analyses unfeasible. Table 3 shows the percentages of each priority after the study's delimitation.

Another important point is that during triage, for green and blue patients, who are considered non-urgent cases, the nurses offer a referral to a primary health center. This is a hospital strategy to try to reduce the number of non-urgent patients and occurs after the Manchester priority level has been identified, although, according to the data, only 3% of patients agree to be referred.

4.2.4 Diagnostic approach and treatment. The next phase, named as Diagnostic/Treatment, is the most complex and involves the greatest variety of possible patient flows. Its characterization depends on various records made by different professionals and systems, which makes the database unreliable. Consequently, the existing time records basically included the start time of the first medical observation and the outcome time of the emergency episode, creating a "black box" of activities that could not be detailed. Some of

Table 3. Percentage of patient according to Manchester triage protocol

Priority	%
Green (non-urgent priority)	43,73
Yellow (urgent priority)	49,81
Orange (very urgent priority)	6,46

Source(s): Authors' own work

the activities that may occur between these two moments (medical observation and outcome) include complementary exams, medical procedures, nursing procedures, medical re-evaluations, and waiting times. The performance of these activities depends on factors such as the patient's complaints, the flowchart and priority defined during triage, and the availability of resources.

Due to the lack of detailed registered information about the activities performed and the time spent, a data fit decision was adopted (named here has "black box"), wherein patients undergo an initial medical consultation, general procedures (which include waiting times and exams, for example), and a second medical consultation for the final assessment Figure 4 represents this model, validated with the hospital team. Thus, for the different flowcharts and priorities of the Manchester scale, a similar procedure to triage was performed, defining the duration of the "black box" using the maximum likelihood method to determine distributions that represented the sample. Once the duration of the black box was obtained, the time was divided into 15% for the first medical observation, 80% for the procedures, and 5% for the final medical observation. Finally, an additional adjustment was made to set a minimum duration for medical consultations at 10 min, as the distribution sometimes generated very low values that did not reflect reality. These values were estimated based on conversations with healthcare professionals and scientific literature (Castanheira-Pinto *et al.*, 2021), serving as an initial approach to detailing the "black box."

With this approach, even without detailing the activities that occur between the initial consultation and the patient's discharge, it was possible to characterize the durations of this stage. This achieved a representation of the behaviour that allows for the proportional allocation of resources according to the time spent.

4.2.5 Patient discharge. The final stage, after the follow-up consultation and the discharge of patients, can result in either discharge or referrals and hospital admissions, for example. The provided data indicated the assigned destination for each patient, which allowed for quantification and assessment of its impact on the service. The following discharge destinations were classified in six groups: discharge with referral to primary care (52.13%), discharge (28.26%), admission for hospitalization (10.88%), discharge with referral to outpatient consultation (6.01%), transfer to another hospital (2.46%) and discharge with home care services (0.26%).

Although patient discharges usually do not require waiting, allowing the patient to leave as soon as they receive their referral, this is not the case for admission to hospitalization. In this scenario, the entry time into the inpatient service was recorded, allowing the authors to quantitatively estimate the duration from when a patient was recommended for hospitalization until they occupied a bed. This time was characterized by a distribution and is relevant because while the patient waits for a place in inpatient care, they continue to occupy physical space in the emergency department.

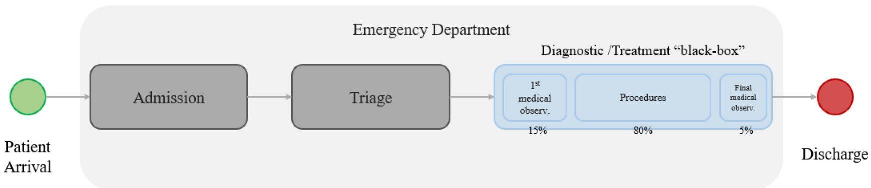

Figure 4. Detailed patient flow
Source(s): Authors' own work

Finally, the exits categorized as "death" and "abandonment" were also characterized in the database, but these were very rare. Therefore, they were not considered in the simulation model.

4.2.6 Complementary data analysis. The available data also includes characteristics of patient flow related to other departments of the hospital, such as the need for imaging exams, blood analysis and medical assessments outside of the ED, which are considered within the described "black box". Although the model focuses on the ED, understanding these relationships is crucial for characterizing patient flow and its impact on the average length of stay (ALOS). In addition, obtaining detailed data on some of these activities, particularly blood analysis and imaging exams, is quite complex. Initial analysis indicates that most patients undergo these activities during their ED visit, with the frequency increasing according to the higher complexity of the patients.

In this context, due to the lack of duration data for these activities, the researcher performed an independent t-test to compare the ALOS of patients based on their flow characteristics. The results are presented in Table 4, with a p-value for the statistical test < 0.05.

The results compare the ALOS of patients who met the criteria with those who did not, showing that all these factors resulted in a longer time spent in the ED.

4.3 DES model development

Based on the initial understanding and data analysis, a simulation model was developed using Simio® software, which includes both the physical modelling and mathematical characterization of the ED. Figure 5 represents the final model.

The previously calculated quantitative values were inputted using the functionalities of the software. Table 5 summarizes the main duration inputs of the model. In addition, the resources presented on Table 2 were also included in the model.

In addition to these initial characteristics, logical processes were implemented to represent decision-making, incorporating the percentages presented in the previous chapter, such as the number of patients assigned to each priority level on the Manchester scale. The main modelling decisions included verifying whether patients had red priority upon hospital entry, which allows them to bypass admission and triage; checking the availability of physical space in all rooms; and assessing the availability of resources to perform the required activities. The sharing of medical resources was also modelled, serving both green and yellow patients, ensuring they are attended to according to predetermined criteria. Moreover, the possibility of patients being internally transferred within the ED after the first medical consultation was added, such as a yellow patient from general practice being referred to internal medicine.

After developing the model, validation was conducted by generating a standard scenario with the current hospital resources and simulating for one year. The obtained values were

Table 4. ALOS

Criteria (comparison between patients who had these characteristics and those who did not)	ALOS additional time (minutes) (CI 95%)
Retriage (n = 585)	80,644 +/− 19,651
Medical Assessment outside of ED (n = 3280)	159,392 +/− 11,495
Laboratory Analysis (n = 37419)	245,057 +/− 2,962
Radiology Exams (n = 46586)	123,635 +/− 3,090
Hospitalization (n = 7378)	151,690 +/− 6,806

Source(s): Authors' own work

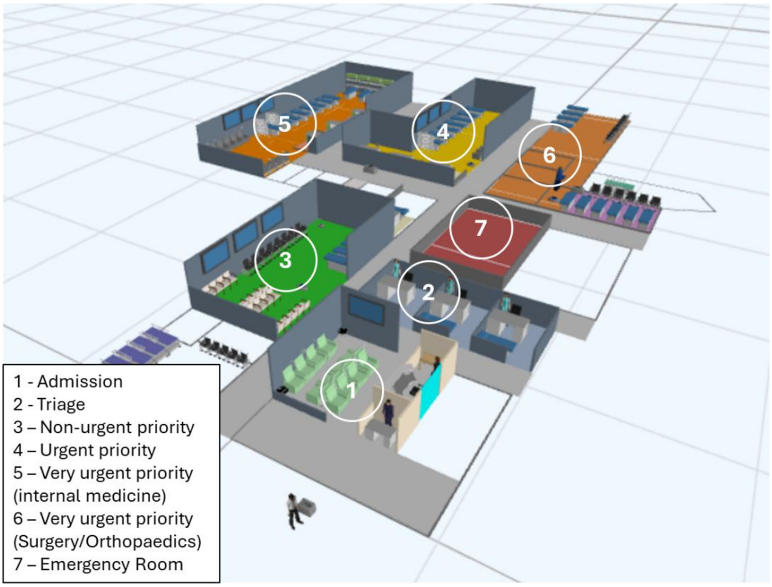

Figure 5. Model overview
Source(s): Authors' own work

Table 5. Model duration inputs

Stage	Duration
Admission	Triangular distribution validated with the professionals
Triage	Non-normal distribution defined by maximum likelihood
Diagnostic/Treatment	Non-normal distribution defined for combinations of flowchart and colour, divided into 15% for the first consultation, 80% for procedures, and 5% for the last consultation
Discharge	Duration only for inpatient admission, non-normal distribution defined by maximum likelihood

Source(s): Authors' own work

similar to the database and confirmed by hospital professionals, indicating that the model adequately represented the ED's functioning.

Overall, the average waiting times for medical care in this case follow the guidelines regulated by the Manchester Triage Protocol: Green priority 1.89 h; yellow priority 1.03 h; and orange priority 0.02 h. However, the average time for yellow priority patients, who represent 49.81% of admissions and over 40,000 cases annually, is close to the target time regulated by the protocol, suggesting an increased need for strategic attention in the service of these patients by the hospital managers.

Based on these results, hypothetical scenarios were simulated to investigate the implementation of changes in the service and to explore the factors influencing patient flows, allowing for a deeper understanding. The results obtained in each experiment were compared with the reference values (standard scenario) to understand the feasibility and impact of these changes on the service.

4.4 Patients' flow analysis

Patient flows are of utmost importance in hospital operations management and have been previously characterized for emergency departments (Lima *et al.*, 2024). Once the model was validated, this research will explore the relationship between variables that impact patient flow, aiming to identify areas for improvement and provide a more detailed characterization of these relationships, using waiting times and LOS as parameters.

4.4.1 Variation in the number of medical resources in green/yellow rooms. As previously mentioned, a number of doctors are shared to attend to green and yellow patients, who account for more than 80% of ED admissions and typically have high waiting times due to their lower priority. Therefore, the number of doctors was varied to explore the impact of increasing and decreasing this resource, creating six scenarios, with the results presented on Table 6:

- *Scenario 1 and 2*: Hypothetical situations of removing one doctor from the day shift and one doctor from the night shift, respectively, while maintaining the number of doctors in the opposite shift.
- *Scenario 3*: Hypothetical situation of transferring one doctor from the night shift to the day shift, thus keeping the total number of doctors the same.
- *Scenario 4 and 5*: Hypothetical situations of adding one doctor to the night shift and one doctor to the day shift, respectively, while maintaining the number of doctors on the opposite shift.
- *Scenario 6*: Hypothetical situation of adding one doctor to both shifts.

The analysis indicates that the variation in the number of doctors has a direct impact on the average waiting time for patients. In scenarios where the number of doctors on the night shift remains constant and only the number of doctors on the day shift varies (1 and 5), it is observed that the average waiting time for medical attention for both green and yellow wristband patients shows an inversely proportional relationship to this variation. That is, a reduction in the number of doctors during the day shift (Scenario 1) results in a significant increase in the average waiting time for medical attention, and the opposite occurs when the number of doctors in the day shift is increased (Scenario 5), as expected.

Table 6. Variation in the number of doctors

Scenario	Physicians (day)	Physicians (night)	Average waiting time green wristband (h)	Average waiting time yellow wristband (h)	Average line green patients	Average line yellow patients
0	6	5	1,89	1,03	6,47	6,06
1	5	5	4,64	1,98	12,99	11,38
2	6	4	2,88	1,82	8,83	9,49
3	7	4	1,68	0,92	5,37	5,10
4	6	6	2,28	0,77	7,16	5,15
5	7	5	1,48	0,93	4,93	5,37
6	7	6	1,48	0,93	5,10	5,52

Source(s): Authors' own work

Overall, adding a doctor impacts green and yellow priority patients differently, depending on the shift in which this change is made. When a doctor is added to the night shift (Scenario 4), the average waiting time for yellow-priority patients decreases compared to the standard scenario, whereas the average waiting time for green-priority patients increases, exceeding the target time defined by the Manchester Triage Protocol. On the other hand, when a doctor is added to the day shift (Scenario 5), the average waiting time for green priority patients decreases relative to the standard scenario. The average waiting time for yellow priority patients also decreases, but less significantly compared to the result obtained in Scenario 4.

Conversely, removing a doctor from the team, regardless of the shift in which this change occurs, promotes an increase in the average waiting times for medical attention for both categories of patients (Scenarios 1 and 2), exceeding the guidelines defined by the Manchester Triage Protocol.

Furthermore, reallocating a resource from the night shift to the day shift (Scenario 3) promotes a reduction in the average waiting times for medical attention for both green and yellow wristband patients, complying with the target times defined by the Manchester Triage Protocol. In addition, the addition of only one doctor to the day shift and the addition of one doctor to both shifts (Scenarios 5 and 6) produce very similar results in terms of the average waiting time for medical attention for both categories of patients.

4.4.2 Reduction in the number of green priority patient episodes admitted to the emergency service. The analysis of emergency episodes recorded over the considered period revealed that more than 40% of these episodes were of a non-urgent nature. This indicates that these patients did not seek the appropriate healthcare facility, contributing to the overcrowding of the service, negatively impacting the quality and efficiency of the healthcare provided, and increasing waiting times and resource consumption. In this context, an evaluation was conducted to determine how a reduction in the number of non-urgent episodes would impact the performance of the ED.

Therefore, scenarios were developed with a gradual reduction in the number of green-priority patients admitted to the service. In each scenario, the number of green priority patients was successively reduced by 10%, up to a maximum reduction of 90% from the initial number, representing a residual presence of these patients in the service. The results obtained are presented in Figure 6.

Analysing the results obtained, a decreasing trend in the average waiting time for both green and yellow priority patients is observed with the reduction in the number of green priority patients. This behaviour aligns with expectations, as a reduction in the number of green priority patients translates to a decreased demand for medical services, reducing the size of waiting lines and consequently the average waiting times for medical attention, alleviating pressure on shared resources, as inferred by the observed reduction in the occupancy rate of doctors.

Green and yellow priority patients represent more than 80% of the total number of admissions to the ED and are responsible for the long average lengths of stay in the service. As previously observed, a reduction in the number of green-priority patients positively impacts not only their own average waiting times but also those of yellow-priority patients. Given that these two groups of patients represent such a significant and expressive part of the ED, it is also noted that these decreases in waiting times for both groups consequently reduce the total ALOS for patients in the service. Thus, the number of non-urgent episodes has widespread repercussions on the overall performance of the ED.

4.4.3 Impact of waiting time for inpatient admission. One of the recurring factors in the literature regarding the causes of overcrowding in emergency departments is the waiting time for inpatient admission (Lindner and Woitok, 2021; Savioli *et al.*, 2022), during which

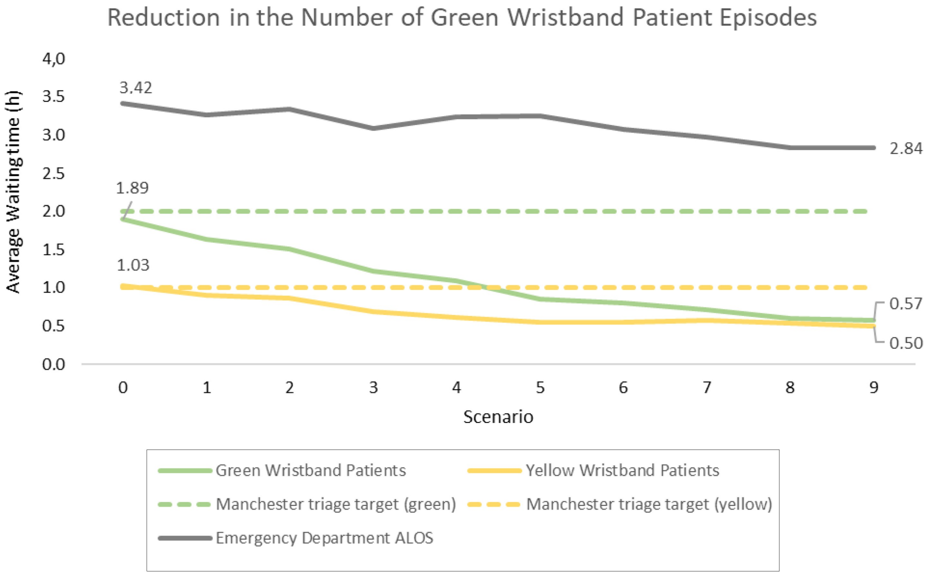

Figure 6. Reduction in the number of Green-Priority patient episodes admitted to the emergency service results
Source(s): Authors' own work

the patient continues to occupy space in the ED while awaiting transfer. In the studied case, the waiting time was calculated by taking the difference between the assigned time for inpatient admission and the time the patient was accepted by the department, resulting in 332.8 min in average. This waiting time was then defined as following a log-logistic distribution with parameters location and scale, respectively, 9.492 and 0.5420, results in seconds). Therefore, gradual reductions of 10% (in average 33.28 min) in the waiting time for inpatient admission were implemented to observe the impact of this delay on the LOS and room occupancy, as shown in Table 7.

Analysing the previous table, it is observed that a reduction in the delay of transferring patients to the Inpatient Service generally results in a successive decrease in the ALOS, with a maximum difference of almost 1 h. This highlights the significant impact that prolonged stays of these patients in the ED have on the overall system performance. In addition, a reduction in the average occupancy of treatment room capacity is also observed, indicating that the waiting time for inpatient admission directly affects the level of overcrowding in the ED.

4.4.4 Impact of combined improvements. Finally, the scenarios involving a reduction in green patients and a reduction in inpatient admission time were combined to explore how the ED could perform with both improvements, either fully or partially implemented, as shown in Table 8.

The results show a better performance, reducing the ALOS from 3.55–2.31 h, which corresponds to an improvement of 34.93%. In addition, the occupation of the rooms was reduced, highlighting the opportunity for improvements in the operations of the ED.

5. Discussion

Resource limitations are one of the major challenges in hospital operations management. In the case of human resources, doctors are a critical and typically scarce profile. Their

Table 7. Reduction of inpatient admission time in the ED in hours

Scenario	Time reduction factor (applied to the result of the distribution)	ED simulated ALOS (hours)	Green room occupancy (patients)	Yellow room occupancy (patients)	Orange (internal medicine) room occupancy (patients)
0	1	3,72	6,41	9,26	3,07
1	0,90	3,54	6,16	9,31	3,07
2	0,80	3,56	6,27	9,30	3,06
3	0,70	3,31	6,13	8,93	3,05
4	0,60	3,31	5,94	9,04	2,98
5	0,50	3,27	6,02	8,82	3,06
6	0,40	3,18	5,93	8,62	3,07
7	0,30	3,11	5,82	8,53	2,96
8	0,20	3,03	5,76	8,22	2,93
9	0,10	2,98	5,51	8,13	2,91
10	0,00	2,87	5,27	7,71	2,84

Source(s): Authors' own work

Table 8. Results of combined improvements

Scenario	Reduction in the number of green-priority patients	Time reduction factor (applied to the result of the distribution)	ED simulated ALOS (hours)	Green room occupancy (patients)	Yellow room occupancy (patients)	Orange (internal medicine) room occupancy (patients)
0	1	1	3,55	6,40	9,06	3,06
1	0,90	0,90	3,37	5,53	9,01	3,04
2	0,80	0,80	3,09	5,02	8,86	3,01
3	0,70	0,70	3,03	4,48	8,82	3,09
4	0,60	0,60	2,87	3,61	8,77	3,04
5	0,50	0,50	2,81	2,90	8,77	2,99
6	0,40	0,40	2,65	2,40	8,51	2,97
7	0,30	0,30	2,66	1,67	8,68	2,90
8	0,20	0,20	2,57	1,12	8,43	2,92
9	0,10	0,10	2,41	0,54	7,83	2,90
10	0,00	0,00	2,31	0,00	7,60	2,81

Source(s): Authors' own work

efficiency depends on systems and patients' factors such as the entry rate, complexity, number of patients and service time (Taiwo *et al.*, 2023). Moreover, their time is shared between different clinical and administrative tasks that could be supported by other professionals (Johnsgård *et al.*, 2024). Since the entry rate in the ED is variable due to spontaneous demand, resource planning becomes complex, with peaks and valleys in allocation. This behaviour is evident with the simulation model, highlighting the difference between morning and night shifts. There are strategies for allocating doctors adopted in some institutions, which require an understanding of the entry rate and treatment time to maintain service quality. In this sense, simulation has proven to be a viable tool for comparing allocation scenarios using process indicators, thus enabling a more efficient ED.

ED overcrowding is a recurring and well-studied issue in the literature, caused by factors such as the lack of inpatient beds, resource shortages, and waiting times for complementary diagnostic procedures (Lindner and Woitok, 2021; Morley *et al.*, 2018; Savioli *et al.*, 2022). Among these, in this study authors highlight the impact of inpatient waiting times, noting that patients who should be transferred are occupying ED spaces due to issues in other departments (Ansah *et al.*, 2021; Morley *et al.*, 2018). This suggests the need for studies that encompass patient flow post-ED (Samadbeik *et al.*, 2024). It underscores one of the many connections the ED has with other departments, often serving as the hospital's entry point. The model allowed for the quantitative simulation of scenarios reducing this waiting time, showing an average difference of nearly one hour in LOS between the current scenario and the scenario where the patient is transferred immediately after the medical referral. Therefore, bed allocation strategies in the inpatient service are essential for improving the ED, ensuring there is a margin to receive emergency patients. Data analysis shows that other factors such as the need for transportation, complementary exams and consultations with specialists not part of the ED team increase the ALOS, further reinforcing the connections between this department and other hospital services. This was validated by the simulation model, which demonstrated improvements in the ALOS after implementing improvements across several scenarios.

Some of the factors that contribute to the overcrowding are the arrival patterns, volume and complexity (Taiwo *et al.*, 2024), leading to several strategies to face this challenge (Morley *et al.*, 2018). In the studied case, there is an initiative to reduce non-urgent patients (Manchester classification blue and green) by referring them to primary care, as suggested by some authors (Ansah *et al.*, 2021). This group represents more than 40% of admitted cases and could be treated outside the hospital context. The model allowed for exploring the impact of this policy on the service by gradually increasing the number of referred patients. Results indicate that a reduction of 40% in this group could enable the reallocation of a doctor during the night shift. Moreover, this reduction improves the metrics for yellow priority patients, as doctors are shared between the two groups. Some studies show that patients already sought care guidance before moving to the ED, but there is a lack of research on the pathways before the arrival of patients (Nummedal *et al.*, 2024b). Several studies have explored interventions to reduce ED number of arrivals, many focusing on frequent users and specific medical conditions (Nummedal *et al.*, 2024a). Although various reasons lead non-urgent patients to the ED, this model data quantify the consequences and impact on the system, reinforcing the importance of integrated medical systems.

Finally, data analysis and other developed experiments confirm aspects previously discussed in the literature. Triage plays an important role in the flow and in the LOS and should be sized attentively (Rowe *et al.*, 2011). The contact time between doctor and patient also significantly impacts resource allocation, although it is a complex factor to discuss, once there is a trade-off that extends beyond process optimization and needs deeper exploration to avoid compromising service quality. In addition, data analysis reinforced the impact of aspects as complimentary exams in the LOS, which can be related to an overuse of imaging auxiliary exams (Kwee *et al.*, 2024)

6. Conclusions

This article studied patient flows in the emergency department using a Lean healthcare approach and discrete event simulation. By using lean tools such as process modelling, Gemba walking, data analysis and modelling the system, it was possible to explore the relationships between factors that influence wastes, such as waiting time and total LOS. LOS is equivalent to throughput time, and reducing it is directly related to reducing work-in-process. Medical resources are scarce and critical for operation, making their allocation according to service entry rates crucial. In addition, resource sharing improves the ED's efficiency, allowing for optimized care for non-urgent patients. The results showed the impact of non-urgent patients on the service, accounting for over 40% of admissions and affecting average times and resource allocation. Another factor exacerbating overcrowding is the waiting time for inpatient admission, which can increase the ALOS in the ED by up to one hour. Although triage was not a bottleneck in this case study, it should be carefully scaled, as it significantly impacts patient flow. The utilization of the patient flows model for studying different scenarios for wastes reduction allowed to verify the impact for improvement of hospital operations and enhancement of the patient experience. These findings reinforce, detail, and complement previous research, providing a better understanding of the impact of certain factors on patient flow and hospital operations management.

Despite the results obtained, this article presents some limitations due to the method and data availability. Firstly, the case study is context-specific; however, the lessons learned are relevant to other cases. Additionally, the authors aligned modelling decisions with the generic flowchart proposed by Lima *et al.* (2024), so it can be adopted in other institutions in the future. Another limitation is the lack of data after the first medical consultation, which required the use of a "black box" structure. The use of the maximum likelihood method for the Manchester flows and priorities is a way to reduce and characterize the sample, but it is still an approximation. Although the values represent the studied hospital, future research can explore the black box percentages in detail, characterizing it with more information. Possibilities for this include manual data collection or the use of patient location technologies to obtain complete end-to-end process data. Another point is the characterization of human resources for Diagnostic/treatment. The model only considers the "doctors" resource, but during an emergency episode, various professionals are involved, such as those administering medication, providing transport, or performing cleaning tasks. The researchers acknowledge that all these professionals are important, but to avoid an overly complex model, they chose to adopt the doctor as the representative resource, being the scarcest and most costly in the studied context. Finally, the data obtained were from a one-year period, which limits both the sample size and may change over time.

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