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ARTICLES

DISCRETE EVENT SIMULATION TO ANALYZE PATIENT PRIORIZATION IN THE CONTEXT OF AN EMERGENCY DEPARTMENT

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ABSTRACT. With the growth of the demand flow and its variability at an emergency department, the complexity to deal with the prioritization of assistance also increases, seeking to offer a quality service. In this sense, several systematized risk triage protocols were created to organize the queues at the emergency, establishing an order of service to ensure that patients do not wait more than a safe time to receive their first medical care. Therefore, the objective of this work is to analyze and evaluate the behavior of an emergency department using a discrete event simulation model. For the results, it was possible to better understand the patient flow, identify problems and difficulties in the system, propose alternatives to deal with patient prioritization, and evaluate the performance of these alternatives through the Goal Question Metric methodology.

Keywords: emergency department, patient prioritization, discrete event simulation.

1 INTRODUCTION

The pressure on the emergency department has grown considerably in recent years in response to increasing demand and its variability, resulting in overcrowding, delays, and long queues, making this ward one of the most critical and congested areas of a hospital. Overcrowding in the emergency department prevents the timely delivery of health services, affects quality of service

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and user satisfaction, and has become an international problem (Zeinali et al., 2015; Lin et al., 2015; Vanbrabant et al., 2019).

Therefore, reducing the waiting time of patients for health services is an important public policy issue for most OECD countries, allowing a better experience for the patient, who does not feel that they are waiting for long periods to have their health problem diagnosed or to have access to a treatment that allows them to improve their quality of life (OECD, 2020). In this sense, it is crucial that there is a system to determine the order of care in the ED, and that it is not only based on the order of arrival but the order of clinical needs. According to Xavier et al. (2019), the non-distinction of risks or degrees of suffering causes some cases to get worse in the queue, sometimes even causing people to die due to lack of timely care. So, risk classification has been used in several countries, including Brazil.

Several systematized risk triage protocols have been created to organize the queues in the ED, establishing an order of care that ensures that patients do not wait longer than a safe time to receive the first care. Triage is a system that performs clinical risk management of patients who are received in the ED, to ensure care according to the patient's needs and within a timely manner (Cordeiro et al., 2014). There are five risk classification models most accepted worldwide: the Australasian Triage Scale (ATS); Canadian Triage Acuity Scale (CTAS); Manchester Triage System (MTS); Emergency Severity Index (ESI) and the Andorra Model (Model Andorrà del Trialge - MAT). These models range from two to five levels of severity (Cordeiro et al., 2014; Mackway-Jones et al., 2013).

The Manchester Model is one of the most used in Brazil and presents five categories of signs and symptoms based on a patient's complaint or presenting situation (Amorim et al., 2019; Pereira et al., 2022; Bouzon Nagem Assad & Spiegel, 2020). Each category is associated with a number, a color, a name, and a maximum time for the first contact with the physician. Among the various aspects of the EDs, it is important to allocate the patient into one of the categories, which will affect the order of care and guarantee the patient the first care within a safety time range (Cordeiro et al., 2014; Mackway-Jones et al., 2013).

The general objective of this paper is to analyze the behavior of an emergency department that makes use of the Manchester model to classify the risk of patients. Two specific objectives are assumed. The first is to model a computer simulation of the operation of an emergency department under the aspects of the Manchester model and evaluate its performance. The second is to implement solutions in the computer simulation model to improve patient care time and analyze them.

To achieve the objectives, this research uses quantitative models (abstract models described in mathematical and computational language). These models are used to assist in the decision-making process. That is, they seek to determine the best way to design, plan and operate systems, usually under conditions that require efficient allocations of scarce resources (Morabito & Pureza, 2010). According to Martins (2010), the most appropriate research methods, in operations management, to conduct quantitative research are survey research; modeling and simulation; experiment, and quasi-experiments. Specifically, in this work, modeling and simulation are used, where there is the manipulation of variables and their levels by the researcher, but not of reality. Goal Question Metric Methodology (GQM) was used to analyze the performance of the simulation model (Van Solingen et al., 2002).

For Hillier & Lieberman (2021), simulation is an operations research technique that uses a computer to imitate the operation of an entire production process (or part of it) or a system. Simulation has been widely used to analyze stochastic systems that will continue to operate indefinitely. Through this technique, the computer randomly generates and registers the occurrences of the various events that drive the system as if they were physically operating.

This paper is organized into six other sections. Section 2 presents the literature review. Section 3 presents the methodology. Section 4 presents the simulation modeling. Section 5 presents the results. Section 6 presents the discussion of the results from the perspective of the GQM methodology and Section 7 concludes the paper and presents future research directions.

The data used in the research is exclusively theoretical, drawn from other studies available in the literature, and not collected from a healthcare unit, which is one of the limitations of this study. However, this research addresses the issue of patient prioritization and its impact on waiting times, distinct from the supporting references, providing an extensive discussion on the results of the models developed to tackle this common problem in an emergency department.

2 LITERATURE REVIEW

Emergency departments are healthcare sectors that provide care services using their resources to stabilize patients with acute illnesses who need emergency treatment. Due to the nature of the service provided and the patient's need, EDs serve on spontaneous demand, without the need for prior scheduling (Mohiuddin et al., 2017).

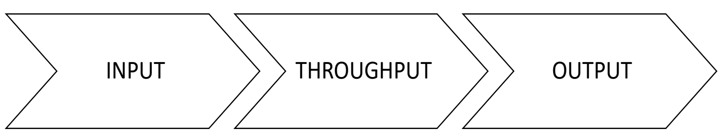

Figure 1 – Conceptual input-throughput-output model

Adapted from Asplin et al. (2003).

First, to manage patient flow in the operational management of the ED, it is common to use a model as a basis to support this flow. This model can be used to analyze the causes and effects of ED crowding, and to evaluate possible solutions. According to Asplin et al. (2003), the input-throughput-output conceptual model (Figure 1) can be applied in emergency services, especially when it comes to their overload analysis and queue management.

The input elements of the conceptual model include any condition, event, or system that characterizes or contributes to the demand of an ED. The transformation components are primarily related to the patient arrival, triage process, diagnosis, and treatment. Finally, the output components concern the aspects related to the admission and discharge of the patient after the care provided (Asplin et al., 2003). In addition, some iterative methods, such as simulation models have been used for planning and optimization in healthcare systems (Zeinali et al., 2015), and can be applied to represent the flow of patients in the operational management of the ED.

Table 1 – Causes of ED crowding.

Components	Factors
Input	Medical/surgical emergencies; urgent visits; non-urgent visits; ambulance arrivals; national “safety net”.
Throughput	Patient acuity; triage and bed placement process; ED bed availability; staffing; diagnostic testing usage; degree of staff training and experience; consultant and ancillary services availability; degree of boarding.
Output	Hospital occupancy; inpatient bed shortages; inpatient team “capping”; staffing ratios; inefficient processes of transferring care to inpatient team; skilled rehabilitation and nursing facility capacity; inefficient inpatient discharge planning; inpatient acuity; need to transfer to higher level of care.

Adapted from Kenny et al. (2020).

In their research, Kenny et al. (2020) examine the causative factors and impacts of crowding in emergency departments. The authors highlight that, for many years, a significant influx of uninsured individuals and those with non-emergent issues were considered the primary sources of crowding. However, this assumption has been debunked on multiple occasions. The authors categorize the causes into three interdependent components that influence patient flow, illustrating the multifactorial and complex nature of these factors. Table 1 outlines the various contributors to each of these three components.

It is worth noting that many of these factors are outside the control of the ED, such as input factors, as well as partnering with outpatient services or requesting an ambulance diversion. On the other side, the fact that throughput depends on all the output factors reinforces the idea that emergency flow is dependent on hospital flow. For this reason, the input-throughput-output model is useful not only for understanding ED flow and crowding but also as a framework for conceptualizing hospital flow and capacity (Kenny et al., 2020).

About the effects, Kenny et al. (2020) comment that research has increased in volume and quality over the past twenty years. They present the effects discussed in the literature categorized into seven domains, as can be seen in Table 2. The impacts of ED crowding can be reflected through-

Table 2 – Key effects of ED crowding.

Domain	Effects
Operational metrics	Longer ED length of stay and longer inpatient length of stay.
Patient outcomes and adverse events	Increased mortality and medication errors.
Quality measures	Worse performance on core Centers for Medicare and Medicaid Services measures. An increased time to pain management for long bone fracture, longer time to critical therapies for patients with severe sepsis, delays in assessment and treatment of pain, delays in definitive therapy for acute myocardial infarction, and decreased rates of hand hygiene.
Access to care	Higher left without being seen, leave before treatment completion, and ambulance diversion.
Patient experience	Worse Press Ganey and Health Care Providers and System scores.
Educational experience	Fewer patients and procedures for emergency medicine residents.
Financial health	Significant financial losses for EDs and hospitals.

Adapted from Kenny et al. (2020).

out the hospital in different ways, affecting its performance and satisfaction metrics. Many of these impacts are systemically linked, producing a negative loop effect.

For Moskop et al. (2019), the consequences of crowding in the ED can be viewed from many perspectives. The authors draw attention to the moral implications of such a problem. ED crowding undermines professional duties grounded in all four fundamental principles of bioethics, most notably beneficence, but also non-maleficence, respect for patient autonomy, and justice.

ED crowding impedes beneficial care in several ways. In crowded circumstances, delays in initial practitioner assessment and patient reassessment are usual, including in pain management situations. Often, patients stay for long periods in the ED until it is time to discharge. Also in crowded ED situations, medication and other medical errors are increased, and these errors can cause serious harm to patients. Moreover, patients admitted to the hospital in this condition have worse outcomes: higher mortality rates, longer hospital stays, and are more likely to leave against medical advice or before completing treatment (Moskop et al., 2019).

Consequently, patients report dissatisfaction in surveys with emergency department and hospital admissions. From a moral perspective, this dissatisfaction may reflect a failure to respect patient dignity or promote patient well-being. In addition, patients are often forced into makeshift treatment areas, such as hallway beds and other shared spaces, where they experience an obvious lack of privacy and control over their personal information. Another relevant consequence of crowding and its direct effects is that it can evoke moral distress, a term used to describe the painful psychological imbalance that clinicians experience when external constraints prevent them from pursuing what they believe is the morally correct course of action (Moskop et al., 2019).

For Mareiniss (2020), added to the already usual problems of ED crowding, emergency departments are the front line in responding to disasters, and today many are already stretched to their limits. The health crisis caused by the COVID-19 pandemic is an example of the ED‘s difficulty in balancing the resources needed to withstand a disaster caused by an infectious disease.

According to Kenny et al. (2020), to develop sustainable solutions to the crowding problem, it is essential to first understand its various causes and effects. Strategies can be separated into micro-level approaches, which are specific to the emergency department, and macro-level approaches, such as hospital bed capacity, infrastructure, technology investments, and system-wide operations.

Table 3 – Representation of the Manchester Triage System (MTS) categories.

Priority	Name	Color	Maximum time [minutes]
5	Immediate	Red	0
4	Very urgent	Orange	10
3	Urgent	Yellow	60
2	Standard	Green	120
1	Non-urgent	Blue	240

Adapted from Mackway-Jones et al. (2013).

An implementation of a risk classification model (in an ED) can be categorized as a micro-level approach. Using the input-throughput-output conceptual model, the triage process is a component of throughput in an ED, and the implementation of a risk classification model has been used to support this process. In Brazil, as mentioned in Section 1, the Manchester Triage System (MTS) has been widely used for this purpose. The main evaluation metric of the MTS is the patient’s waiting time until the first contact with the physician. The MTS seeks to offer the patient a prioritization of care according to his or her complaint or condition, at the risk of worsening his condition or even leading him to death (Nishi et al., 2018). A patient who presents symptoms of myocardial infarction, for example, demands immediate medical attention or a maximum of 10 minutes. The model defines some periods, presented in Table 3, according to risk categories defined for each patient in the triage process.

3 METHODOLOGY

This research uses a quantitative approach divided into two parts. The first part consists of the procedure to build the simulation model, which is based on Hillier and Lieberman (2010). The second part consists of the procedure to analyze the performance of the simulation model built in the first part with data from an emergency department, which is based on Van Solingen et al. (2002).

The first part deals with quantitative modeling, particularly in the context of operations research applied to production management, involving the phases described below (Hillier & Lieberman, 2021):

(a) Phase 1 - Problem definition; (b) Phase 2 - Building the model; (c) Phase 3 - Solution of the model; (d) Phase 4 - Model validation.

About phase 1, the scope, the decisions of interest, the study objectives, and the conceptual model of the problem were defined. The first process is the registration at the health care facility. For this step, the use of the secretary resource is considered. The next process is triage, where there is a decision about the risk category for each patient. Now, the resource is the nurse. The last process considered in the model is medical care, where the physician provides care according to the priority established in the triage stage. Figure 2 presents the patient operational flow.

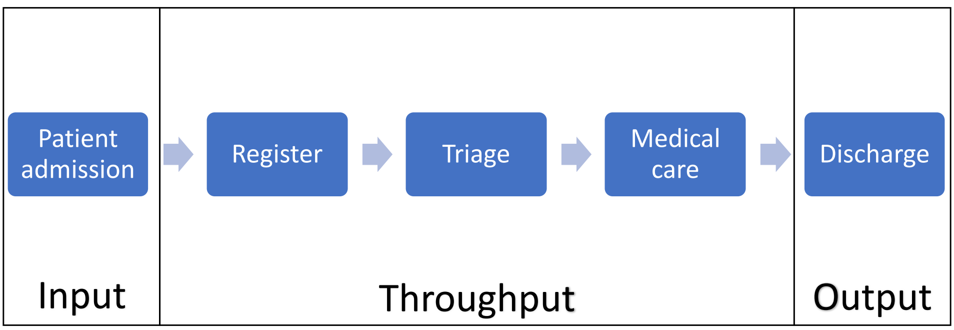

Figure 2 – Patient operational flow based on the input-throughput-output conceptual model.

Prepared by the authors.

The data used in this study were collected using as a reference the research of Ferreira et al. (2020), Cordeiro et al. (2014) and Mackway-Jones et al. (2013). They represent an ED in high patient demand over twelve hours, corresponding typically to the period of a medical on-call. Thus, it is possible to analyze the impact of decisions on the prioritization of caretaking into account their risk classifications and the maximum waiting times until medical attention. These data are exposed in Tables 3, 4, 5, and explained in Table 6.

In phase 2, the model was built to represent the essence of the problem. The model described in this study was built with the support of the Arena Simulation software, which modeling can be done through flowcharts. Three different scenarios were created. The first consists of the basic operating model of the emergency department (without consideration of any solution to improve service time). The other two scenarios present proposals for improving patient care time. In phase 3, a method and algorithms were used to solve the proposed model from the Arena software itself.

Table 4 – Simulation model data.

Process	Resource	Resource Availability	Distribution	Essential parameters	Parameters (values)
Arrival	-	-	Exponential	β is expected value; interval time between consecutive patient arrivals	$\beta = 2.0$
Register	Secretary	2	Weibull	α =scale parameter; δ =shape parameter	$\alpha = 2.3847$; $\beta = 3.0524$
Triage	Nurse	2	Triangular	a=lower limit; b=mode; c=upper limit	TRIA (2,3,4)
Medical care	Physician	3	Gamma	α =shape parameter; β =scale parameter	$\alpha = 3.5956$; $\beta = 1.7646$

Adapted from Ferreira et al. (2020).

Table 5 – Probability distribution by MTS risk classification.

Priority rating	Manchester risk classification system
Red	0.92
Orange	15.71
Yellow	38.19
Green	43.69
Blue	1.49

Adapted from Cordeiro et al. (2014).

In phase 4, it was verified if the model adequately represents the presented problem. That is, to what extent the model describes the behavior of the real system. This phase was done by comparing the service times of the model with the allowed service times of the MTS (Table 3). It should be emphasized that this is a comparison between a theoretical model and a theoretical system. It was not performed in the scope of this work as a comparison with data obtained in the practice of a real system.

This study consists of a theoretical problem for analysis purposes and to support decision-making. Because it is theoretical, the limitations of this first part of the methodology are as

Table 6 – Data collected and bibliography source.

Data collected	Bibliography source
Resources availability; Distributions; Parameters values	Ferreira; Santos; Santos; Reis (2020)
MTS categories and time information Probability distribution by MTS risk classification	Mackway-Jones; Marsden; Windle (2014) Cordeiro; Torres; Rausch (2014)

Prepared by the authors.

follows. The first limitation is that phase 4 was carried out based on a comparison with theoretical data. A second limitation consists in the fact that Hillier & Lieberman (2021) model also includes the fifth phase of solution implementation. This is a critical phase, in which the model is implemented in the organization's practice, translating the results proposed in the model into real gains or decisions. In the present work, this step was not carried out. Thus, we start from the conclusion of phase 4 (that the model is validated) to the second part of the methodology.

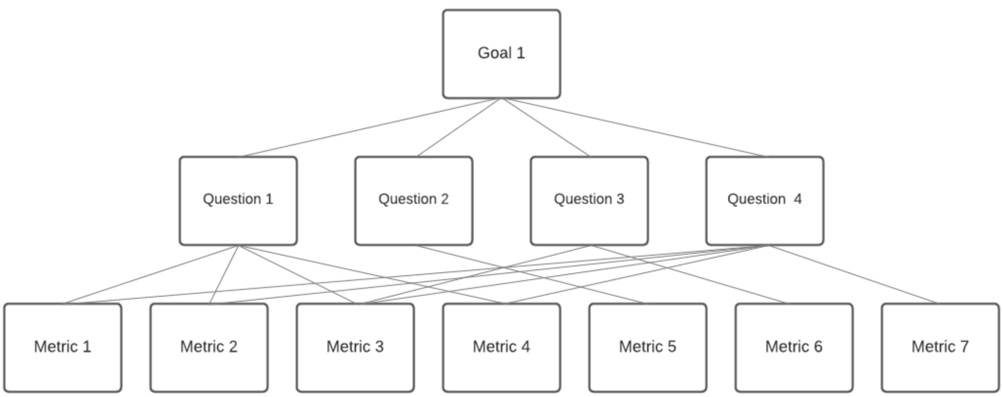

Figure 3 – Hierarchical structure of the GQM in the present work.

Prepared by the authors.

To perform the second part of the methodology, which consists of analyzing the performance of the simulation model built in the first part, the Goal Question Metric Methodology (GQM) was used. According to Van Solingen et al. (2002) the GQM assumes that for an organization to measure intentionally it is necessary to follow a few steps: specify goals (Goal) for itself and its projects, generate questions to track the data (Question), and finally develop a structure (Metric) to track the obtained data. The methodology consists of a hierarchical structure that starts from the definition of the Goal, then unfolds into questions, and then unfolds into metrics. The metrics can be related in the sense of answering one or more questions, just as the questions can be related to the fulfillment of one or more goals. In the present work, goals, questions, and metrics were developed and are related according to Figure 3.

Goal G1 is then to analyze the performance of the computer simulation model of the ED to understand the quality of patient care. Four questions (Q1 to Q4) were developed to address this goal G1. To calculate the metrics and proceed to answer the questions, the three scenarios were simulated for twelve hours and with ten replications. Section 4 presents the characteristics of each simulation scenario and Section 5 presents the results of the analysis. Metrics M1 to M7 have been defined to help answer the questions. Metrics M1, M2, M3, and M4 are related to Q1. Metric M5 relates to Q2. Metrics M3 and M6 are related to Q3. And metrics M1, M2, M3, M4, and M7 are related to Q4. Table 7 presents the descriptions of each question and each metric used in the methodology.

4 SIMULATION MODEL

As mentioned in section 3, three simulation scenarios were built. There is no difference between the data presented in Table 4 for each scenario, being the same amounts of resources and the same probability distributions. The three scenarios will be described in later subsections.

It is worth highlighting some decisions regarding the simulation model. Identifying a precise warm-up period and determining a stationary period posed challenges. Due to this difficulty and the acknowledged imbalance between patient demand and service capacity in the hospital, the decision was made to incorporate the entire simulated period of 12 hours without a designated warm-up phase.

Furthermore, ten replications of the simulation were conducted. No significant changes were identified in the mean, minimum, and maximum values found, with only a reduction in the measure of dispersion, as this is a function of the number of repetitions in the denominator.

4.1 Scenario 1

For the first scenario, the Arena Simulation modules were used: Create, Process, Decide, Assign, Station, Record, and Dispose. In this scenario, we can visualize the arrival of patients, then the registration process, where there is a first queue formation. Soon after, the patient enters the triage process, forming a new queue. At this stage, there is a decision to be made by the nurse resource related to the patient's risk classification. This decision is represented by the decide module and follows the probability distribution in chart 3.

After this decision, the patient receives two attributes in the system. The first one changes the entity, turning ”patient” into ”red patient”, for example. The second gives that patient a risk attribute from 1 to 5, with 1 being blue and 5 being red.

By following the patient's flow, he or she arrives at the doctor's office, forming a new queue for this resource. The record module (called a report) was used only to count the patients and at the end, we have the output of the system entities.

Table 7 – GQM Goals, questions and metrics.

Name	Description
Goal 1 (G1)	To analyze the performance of the computer simulation model of the ED to understand the quality of patient care.
Question 1 (Q1)	What is the perceived level of quality of patient care in each scenario?
Question 2 (Q2)	What is the bottleneck resource in the simulation model?
Question 3 (Q3)	How well does the simulation model adhere to the Manchester model?
Question 4 (Q4)	Which scenario has the best quality of patient care?
Metric 1 (M1)	Proportion of patients attended. Calculated for each risk category of the Manchester model, averaged across replications, and for each scenario. It represents the percentage of patients attended in each risk category about the total number of patients in each scenario.
Metric 2 (M2)	Average waiting time for the patient, from arrival at the hospital (the hospital is aware of the patient's arrival when he/she enters the registration queue), until being seen by a physician. Calculated for each risk category of the Manchester model, averaged across replications, and for each scenario.
Metric 3 (M3)	Maximum waiting time for the patient, from arrival at the hospital (the hospital is aware of the patient's arrival when he/she enters the registration queue), until being seen by a physician. Calculated for each risk category of the Manchester model, averaged across replications, and for each scenario.
Metric 4 (M4)	Percentage difference (deviation) between M2 and M3.
Metric 5 (M5)	Occupancy rate of each resource (percentage of the total simulation time when the resource is occupied). Calculated on average between replications, and for each scenario.
Metric 6 (M6)	Percentage difference (deviation) between M3 and the maximum care time allowed by the Manchester model.
Metric 7 (M7)	Difference in minutes (deviation) between the M2 values calculated for each scenario.

Prepared by the authors.

4.2 Scenario 2

For the second scenario, the Arena Simulation modules were used: Create, Process, Decide, Assign, Hold, Station, Record, and Dispose. The initial and final parts of the model are the same as the first scenario. The main difference between the scenarios refers to the implementation of waiting rooms (represented by the Hold module) after the risk classification of patients.

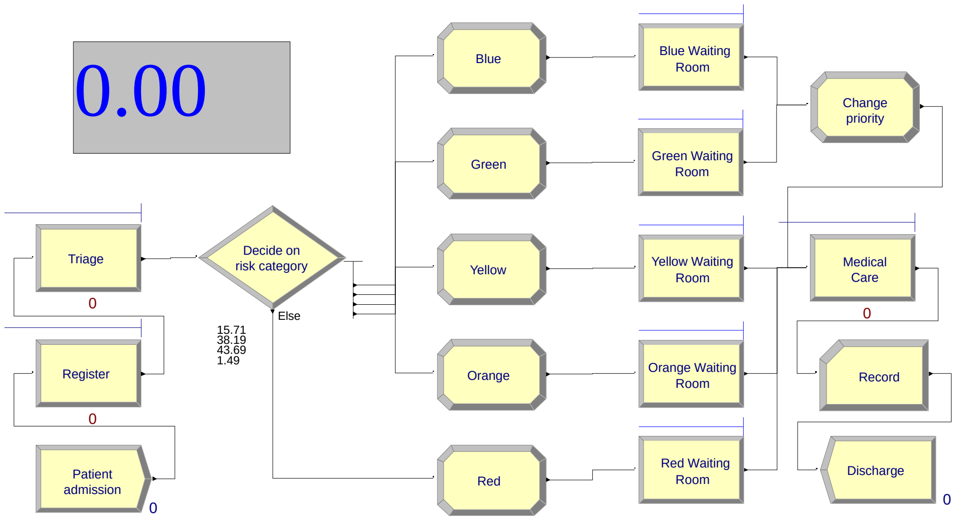

Figure 4 – Arena’s developed model for scenario 2.

Prepared by the authors.

This change sought to solve the problem of the low attendance rate of patients with lower priority, who ended up at the end of the queue for medical care and, therefore, had higher average waiting times in scenario 1. For a patient to stay in the waiting room or proceed to medical care, some conditional rules were established, as follow.

(a) Red waiting room: a patient that needs immediate attend, no need to wait. (b) Orange waiting room: very urgent patient, no need to wait. (c) Yellow waiting room: urgent patient, no need to wait. (d) Green waiting room: if the queue for medical care is longer than 5 patients, the green patient should wait. However, if he had already been waiting for more than 60 minutes, he could proceed to the service. (e) Blue waiting room: if the queue for medical care is longer than 5 patient, the blue patient should wait. However, if he had already been waiting for more than 120 minutes, he could proceed to the service.

These parameters for the holding area were chosen based on two aspects: firstly, a parameter identifying a situation of excess demand for medical care. For this purpose, the parameter of 5 patients in the waiting queue was selected. With this parameter, patients classified as green and blue did not remain excessively in the waiting queue for this service, as the excess demand led to a continuous care for yellow, orange, and red group patients, without allowing gaps for the treatment of other patients.

The second parameter was necessary to define the moment when the patient could leave the waiting room and change their risk level. This way, the blue, green, and yellow patients would be in the same order of priority. In other words, in addition to the implementation of the waiting rooms, two additional ”Assign” modules were created, which serve to change the priority of blue and green patients upon leaving the waiting room. After the waiting period, according to the established conditions, the blue and green patients receive a new risk attribute, changing their risk classification to 3, the same as the yellow patient. In Figure 4, it is possible to visualize part of the model developed in Arena.

In this sense, the waiting time parameters to leave each room (Blue Waiting Room and Green Waiting Room) could not be the same given the characteristics of each patient (blue and green). Thus, the parameter was define as half of the maximum allowed time, according to the MTS, for each patient group (60 minutes for the green patient and 120 minutes for the blue patient). It’s worth noting that the waiting rooms were treated with infinite capacity, without any limitation on space for patient waiting. This is a simplification of the model, as in real situations, such restrictions should be considered.

4.3 Scenario 3

For the third scenario, the Arena Simulation modules were used: Create, Process, Decide, Assign, Pick Station, Station, Record, and Dispose. In this scenario, again the start of the process was modeled the same as in scenarios 1 and 2. The change analyzed, in this case, was the separation of the medical queues into three separate queues, one for each physician, using the same probability distribution. For this, Arena’s pick station module was used to represent the moment of choice of the queue where the patient would be allocated. This decision was chosen according to the shortest queue and the occupation of the resource. The prioritization of care in all processes was kept the same as in scenario 1, being the red patient the highest priority and the blue the lowest. In Figure 5 it is possible to visualize part of the model developed in Arena.

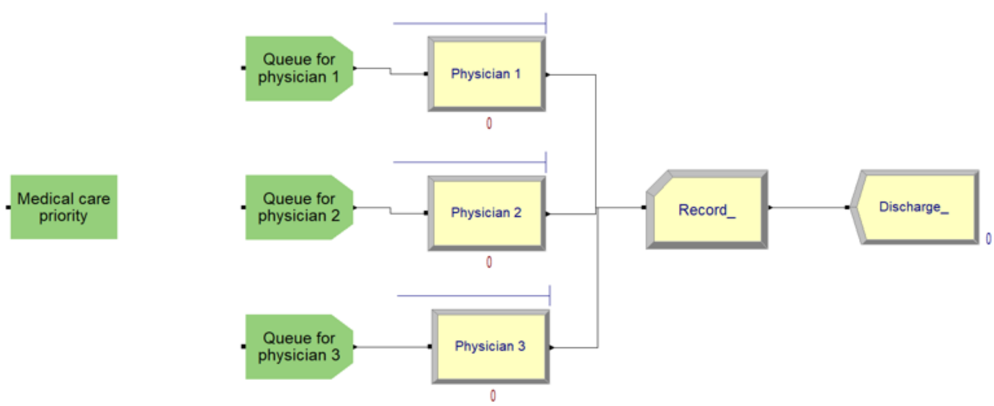

Figure 5 – Arena’s developed model for scenario 2.

Prepared by the authors.

5 RESULTS

In the three scenarios, it was perceived that the bottleneck in the operational flow of the patient is medical care, with the highest occupation rate with resources and with the longest queues. The scenarios sought to present alternatives to deal with the priority of care to meet the requirements imposed by the MTS and reduce the waiting time of patients and increase the rate of care, variables analyzed by risk classification.

Table 8 – Occupancy rate of the resource (M5) physician in the scenarios.

Resource	Scenario 1	Scenario 2	Scenario 3
Physician 1	96.93%	96.93%	99.18%
Physician 2	96.84%	96.84%	98.67%
Physician 3	96.67%	96.67%	98.54%

Prepared by the authors.

In Table 8 it is possible to verify that the three scenarios presented a high occupancy rate of the resource (M5) physician, with scenario 3 presenting the highest rates. The other resources in the three scenarios presented occupancy rates (M5) between 65% and 76%, demonstrating that the bottleneck is in the medical care stage and that the simulation represents a high patient demand.

The results for scenario 1 showed a proportion of patients who attended (M1) of 90.18% with a preference for patients at higher risk, as we can see in Table 9. In Table 10, we can see that the maximum waiting time (M3) of the patients meets the MTS requirements, except for the patient classified as blue, which had a peak waiting time of 384 minutes. During the simulation, it was noticed that during times of high demand for medical care, the patients with low priority, usually those classified as blue or green, took much longer to be attended to because they were waiting for an opportunity of availability from the doctor.

Scenario 2 tried to better deal with this issue of prioritization of care, which includes a low proportion of patients attended (M1) of the least priority patients and higher average waiting times for these patients (M2 and M3), especially those classified as green and blue. It can be seen in this scenario, from tables 9 and 10, that the performance in these variables was better for these less severe patients. However, there was a loss in performance of the variables referring to the patient classified as yellow. Even so, the MTS requirements for maximum waiting time were met even by the maximum times found in the simulation.

Scenario 3, on the other hand, presented the worst performance in all the variables measured, proving to be the worst scenario among the options. This scenario generated large queues and much longer waiting times compared to the others, as we can see in Tables 9 and 10. The simulation of scenarios 1 and 3 shows that the lower the priority of care for the patient, the greater the chance that the patient will remain in queue time. This can be seen both during the simulation and by the maximum and average waiting times shown in Tables 9 and 10. Patients classified as blue, for example, have a low probability in triage, however, since they have a lower priority of

Table 9 – Percentage of patients served (M1) to scenarios 1, 2 and 3.

	Scenario 1			Scenario 2			Scenario 3		
Patient	Number in	Number out	%	Number in	Number out	%	Number in	Number out	%
Red	2.2	2.2	100.00%	2.2	2.2	100.00%	3.33	3	90.09%
Orange	57.3	56.6	98.78%	57.3	56.6	98.78%	60.33	58.33	96.68%
Yellow	139.3	137	98.35%	139.3	124.2	98.16%	135.67	111.67	82.31%
Green	164.7	133.8	81.24%	164.7	144.5	87.74%	145	60.33	41.61%
Blue	4.1	1.9	46.34%	4.1	4	97.56%	3.67	0	0%
Sum	367.6	331.5	90.18%	367.6	331.5	90.18%	347.9967	233.33	67.05%

Prepared by the authors.

Table 10 – Waiting times (M2 and M3), deviation (M4), and percentage difference (M6) in scenarios 1, 2 and 3.

	Scenario 1					Scenario 2					Scenario 3				
Patient	1	2	3	4	5	1	2	3	4	5	1	2	3	4	5
Red	3.15	6.1556	95.42%	0	-	3.15	6.1556	95.42%	0	-	17.291	24.5611	42.05%	0	-
Orange	4.6702	8.0403	72.16%	10	-20%	4.681	8.0403	71.76%	10	-20%	14.8767	17.6317	18.52%	10	760%
Yellow	6.0584	9.3188	53.82%	60	-84%	33.2282	59.145	78.00%	60	-1%	43.4014	47.1579	8.66%	60	-21%
Green	61.5619	112.11	82.11%	120	-7%	46.0615	80.3134	74.36%	120	-33%	137.27	165.8	20.78%	120	38%
Blue	109.52	384	250.62%	240	60%	50.8661	95.9204	88.57%	240	-60%	-	-	-	240	-

Prepared by the authors.
1= Average waiting time
2= Maximum waiting time
3= Deviation [(max-average)/average]
4= Time allowed [minutes]
5= Deviation [(max-allowed)/allowed]

Table 11 – Average waiting time (M2), per scenario and difference in minutes between scenarios (M7).

Patient	Scenario 1	Scenario 2	Scenario 3	Difference between 2 and 1 [2-1]	Difference between 3 and 1 [3-1]	Difference between 2 and 3 [2-3]
Red	3.15	3.15	17.291	0	14.141	-14.141
Orange	4.6702	4.681	14.8767	0.0108	10.2065	-10.1957
Yellow	6.0584	33.2282	43.4014	27.1698	37.343	-10.1732
Green	61.5619	46.0615	137.27	-15.5004	75.7081	-91.2085
Blue	109.52	50.8661	-	-58.6539	-	-
Average	36.9921	27.59736	53.209775	-9.39474	27.47972	-25.14368

Prepared by the authors.

care, they can stay in the queue waiting for the doctor's availability for a long time, waiting for an opportunity of low demand, since they cannot overtake those patients with higher priority in the queue.

However, scenario 2 deals with this issue better by creating waiting rooms and changing the priority of blue and green patients after certain conditions are accepted. Thus, this proved to be a more balanced scenario, where all categories of patients could be seen within the maximum time allowed by the Manchester Triage System. The comparison between the scenarios, especially between the first and the second in terms of average waiting time, can be seen in Table 11.

It should also be noted that the patient classified as red, despite receiving priority of care, presents a small waiting time, but longer than allowed (zero). This is because the system represents a situation of an emergency department with high patient demand and, therefore, despite having priority, this type of patient needs to wait for the doctor to finish the service before being seen, besides already having gone through other processes in the flow of care. Another point worth mentioning is that, since it represents a period of high patient movement in an ED, if this reality is perceived frequently in the system, a suggestion would be to increase the number of resources for medical care, since the occupancy rate was very close to 100% in all scenarios.

So, the Goal Question Metric (GQM) methodology was applied to assist in the analysis of three proposed scenarios. The scenarios were compared based on four questions and seven metrics. The Q2 question consisted in identifying the bottleneck resource in the simulation model, creating longer queues, and impacting more significantly on waiting times (M2 and M3) and patient care within the Manchester model (M6). The occupancy rate was calculated for each resource in each scenario (M5). Thus, it became evident that medical care was the production process constraint, presenting occupancy rates above 96% in all scenarios.

Question Q1 consisted of analyzing the level of perceived quality of patient care in each scenario. Four metrics (M1, M2, M3, and M4) were analyzed. These metrics allowed a broader look at this question, verifying the proportion of patients served by the system (M1), the average waiting time to medical care (M2), and the maximum waiting time to medical care (M3). The M4 metric also analyzes the deviation between M3 and M2 and can be used as a dispersion metric.

A lower level of care was verified in scenario 3, with low performances for M1 and higher waiting times in M2 and M3. Only the patient classified as blue scenario 3 did not present data for M2 and M3, which is due to the low priority given to this patient added to the low production performance. The M1 metric points to a percentage of only 67% of patients attended in this scenario, none of which are among the patients classified as blue.

Scenario 2 showed the most balanced performance. There are no significant differences in M2 for red and orange patients compared to scenario 1, while scenario 3 shows results five times and three times longer than scenario 2 for red and orange patients, respectively. For yellow patients, the average wait time (M2) increases by approximately 27 minutes from scenario 1 to scenario 2, but green and blue patients have approximate reductions of 15 minutes and 58 minutes. These analyses were possible using the M7 metric, which calculates the difference in minutes between the average wait times (M2) for each scenario (see Table 11).

Scenarios 1 and 2 showed higher deviations (M4) between the maximum waiting time and the average time. This is even more critical for the blue patients of scenario 1, who despite having 109 minutes of average waiting time for medical care, it was possible to identify waiting times of up to 384 minutes, a time 60% above the established by the Manchester model (M6). By analyzing the M6 metric, then, it was possible to answer the question Q3, which consisted in investigating how much the modeled system reflected the behavior recommended by the Manchester model.

Scenario 1, therefore, does not perform well on the M6 metric for blue patients. Scenario 3, on the other hand, presents results that demonstrate that, except for the patients classified as yellow, the others would be subject to being served after the time established by the MST. Scenario 2 manages to serve almost all patients within the established timeframe, except the red ones. This is due to certain constraints of the model, for all scenarios, where medical attendance is a step in the patient flow after two previous steps (registration and triage), with attendance and waiting times. Since there is no possibility of any patient going straight to medical care without going through the previous processes, this makes it impossible to provide care, regardless of priority, without waiting.

Finally, question Q4 consisted of identifying which scenario has the best quality of patient care. Given what has been discussed so far, it was identified that scenario 2 presents a more balanced performance picture in the metrics. Some performance similarities can be seen between scenarios 1 and 2, such as the same total percentage of patients attended (M1) and equal or very close waiting times (M2 and M3) for red and orange patients. However, scenario 2 shows worse results for yellow patients to the detriment of better results for green and blue patients, which allows serving all within the deadline set by the MST.

6 CONCLUSIONS

The present work consists of theoretical work for analysis purposes and to support decision-making. The goal was to analyze the performance of an ED computational simulation model to understand the quality of patient care, guided by Asplin et al. (2003) conceptual model, and the Manchester Triage System (MTS), with quite common use in Brazil to classify the risk of patients. Scenario 1 was the first model developed. Prioritization through risk classification allowed the most severe patients to be attended to with more urgency and less waiting time, thus satisfying part of the MTS requirements. Nonetheless, scenario 2 obtained better performance in the metrics analyzed by the GQM. This scenario, then, presented more balanced and consistent results and, despite the limitations of the model, was able to satisfy all the MTS requirements.

Using a discrete event simulation model, it was possible to better understand the patient flow at an emergency department, identify problems and difficulties in the system, propose alternatives (scenarios) to deal with patient prioritization, and evaluate the performance of these alternatives through GQM methodology. In this sense, this work contributed as a support to assist decision-making by hospital managers responsible for emergency departments and to expand the discussions about the quality of care to patients in these departments.

Due to being a theoretical study, the research was limited to analyzing scenarios based on data collected in the literature (Ferreira et al., 2020; Cordeiro et al., 2014; Mackway-Jones et al., 2013). In other studies conducted in Brazil, different proposals have been developed to address overcrowding in emergency departments, such as dedicating a physician exclusively to patients in the green group. Some data, depending on the case of the study, also exhibit variances when compared to the data utilized in this study. However, these discrepancies do not invalidate the proposals presented in this research, which can showcase alternatives to address the issue of prioritizing patients in emergency department overcrowding and discuss the results of these alternatives (Amorim et al., 2019; Pereira et al., 2022; Bouzon Nagem Assad & Spiegel, 2020).

Nevertheless, for future work, it is suggested to validate the models presented using real system data collected through fieldwork in emergency departments. Other studies could also employ more sophisticated mathematical models to define the priority of care based on risk classification and patients' waiting times, with a wide range of possibilities for Operations Research tools.

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