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SIMULATION MODELS FOR PATIENT FLOW IN AN EMERGENCY DEPARTMENT

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SIMULATION MODELS FOR PATIENT FLOW IN AN EMERGENCY DEPARTMENT

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I dedicate it to my family, especially to my grandfather Readir [in memorian], with great pride and gratitude.

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RESUMO

MODELOS DE SIMULAÇÃO PARA O FLUXO DE PACIENTES EM UM DEPARTAMENTO DE EMERGÊNCIA

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Os departamentos de emergência são sistemas complexos com muitas variáveis, sendo um dos serviços mais problemáticos e desafiadores do sistema de saúde, pois há um constante aumento de demanda e uma estrutura insuficiente. A simulação pode ajudar os gestores de saúde a analisar as causas, tomar decisões e propor melhorias sem interromper a rotina do processo. No entanto, principalmente no Brasil, os métodos de simulação no setor de saúde são pouco explorados. A literatura aponta a existência de três métodos de simulação em crescimento que podem avaliar operacionalmente o departamento de emergência. A simulação de eventos discretos (DES), que modela o fluxo do processo, a simulação baseada em agentes (ABS), que modela o comportamento e interação dos pacientes, médicos e equipe técnica e o método híbrido que integra os dois métodos anteriores e possibilita avaliar o fluxo e o comportamento em um mesmo modelo. Essa pesquisa avalia qual o modelo mais apropriado para simular o fluxo dos pacientes em um departamento de emergência. A avaliação considera os critérios de tempo, custo, conhecimento e necessidade de dados. A partir do *background* teórico e dos dados coletados em uma instituição de saúde no estado do Rio Grande do Sul, Brasil, foi desenvolvido um modelo conceitual e construído quatro modelos computacionais de simulação do departamento de emergência. Um modelo utilizando DES, um modelo em ABS, e dois modelos híbridos, um integrando o paciente em ABS e os recursos em DES e outro modelo integrando os pacientes em DES e os recursos em ABS. Os resultados das simulações demonstraram aderência em comparação com os dados reais. Como entrega dessa pesquisa foram comparados os quatro modelos em relação ao tempo, custo, conhecimento e dados. Ao analisar as categorias de simulação, inputs, outputs, desenvolvimento e resultado dos modelos foi construído um *framework* de orientação sobre qual modelo é mais apropriado para cada necessidade dos gestores. Esse *framework* auxilia os gestores e pesquisadores a escolher o modelo de simulação mais adequado para aplicar nos departamentos de emergência, considerando as vantagens e desvantagens de cada método.

Palavras-chave: Modelagem e simulação em Departamentos de Emergência. Simulação de Eventos Discretos. Simulação Baseado em Agentes. Simulação Híbrida.

ABSTRACT

The emergency departments are complex systems with many variables, it is one of the most problematic and challenging services in the health system, as there is a constant increase in demand and an insufficient structure. The simulation can help health managers to analyze the causes, make decisions and propose improvements without interrupting the routine of the process. However, mainly in Brazil, simulation methods in the health sector are little explored. The literature shows the existence of three growing simulation methods that can operationally assess the emergency department. The discrete event simulation (DES), which models the process flow, the agent-based simulation (ABS), which models the behavior and interaction of patients, doctors and technical staff, and the hybrid method that integrates the two previous methods and allows evaluate flow and behavior in the same model. This research assesses which model is most appropriate to simulate the patients' flow in an emergency department. The evaluation considers the criteria of time, cost, knowledge and need for data. Based on the theoretical background and data collected in a health institution in the state of Rio Grande do Sul, Brazil, a conceptual model was developed and four computer simulation models were devised for the emergency department. One model in DES, one model in ABS, and two hybrid models, one integrating the patient in ABS and the resources in DES, and another model integrating the patients in DES and the resources in ABS. The results of the simulations showed adherence compared to the real data. To achieve this research, the four models were compared in relation to time, cost, knowledge and data. When analyzing the simulation categories, inputs, outputs, development, and results of the models, an orientation framework was built on which model is most appropriate for each manager's need. This framework helps managers and researchers to choose the most appropriate simulation model to apply in their emergency department, considering the advantages and disadvantages of each method.

Keywords: Modeling and simulation in Emergency Departments. Discrete Events Simulation. Agent-Based Simulation. Hybrid Simulation.

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ABS	Agent-based Simulation
DES	Discrete Event Simulation
ED	Emergency Department
SUS	Unified Health System

CONTENTS

1 INTRODUCTION

1.1 Context and research problem

Health environments have many variables, limited resources, demand for quality, and a high level of human involvement among patients, doctors, nurses, and other actors (TAYLOR; NAYAK, 2012; ABO-HAMAD; ARISHA, 2013; VERMEULEN et al., 2014; VOSE et al., 2014). Complex systems are composed of subsystems that involve many dynamic elements that interact in a disordered way and that contribute to the structure of a whole (YOLLES, 1999; LADYMAN; LAMBERT; WIESNER, 2013). In complex systems, such as those in the emergency departments, it is difficult to develop a standard model for decision-making. Consequently, decisions can occur by trial and error. Process Simulation is a method to organize the process and assist in decision-making without interrupting the routine (ABO-HAMAD; ARISHA, 2013; YOUSEFI; FERREIRA, 2017). It is a rational method that provides operational analysis, tactics, and strategy for decision-makers (GUL; GUNERI, 2015).

Emergency departments are health services that care for patients with different severity levels twenty-four hours a day, seven days a week (WANG et al., 2015; YOUSEFI; FERREIRA, 2017). It is one of the most problematic services in the health system, as there is a constant increase in demand and an insufficient structure generating overload and dissatisfaction for both patients and assistance resources (RECH et al., 2018). Also, uncertainty about the demand for service can lead to unbalanced use of resources (ABO-HAMAD; ARISHA, 2013; YOUSEFI; FERREIRA, 2017).

Healthcare managers need to continually improve service efficiency due to high pressure to control costs. So they need timely accurate tools to optimize resources in such a complex system. The evaluation of the proposed changes is important before implementation in the real process (ABO-HAMAD; ARISHA, 2013). A simulation is a method that can help with health improvement projects (ALVARADO; LAWLEY; LI, 2016).

The difficulty of managing the problems of the flow of patients and the provision of health services can be eased by simulating (ABO-HAMAD; ARISHA, 2013). This method is used in emergency departments for problems with patient scheduling, bed planning, new facilities, and other operations (GUL; GUNERI, 2015). The emergency departments have different levels of urgency. Usually patients go through the same processes and resources within the hospital. The complexity of these processes and clinical decisions justify the need for simulation methods that support health managers (SALMON et al., 2018).

There are four main methods of computer simulation in health: Systems Dynamics (SD), Discrete Event Simulation (DES), Agent-Based Simulation (ABS), and the hybrid method that is a combination of two or three existing methods. SD operates in a more abstract environment, DES focuses on the operational process and has the potential to assess the flow of patients, and ABS can evaluate the interrelationship between agents in an emergency department (ABO-HAMAD; ARISHA, 2013; ALVARADO; LAWLEY; LI, 2016; BRAILSFORD et al., 2018).

Discrete event simulation (DES) has been widely used in modeling health systems for many years. Efforts to develop models in DES have been advancing since the late 1980s (GÜNAL; PIDD, 2010). This method focuses on the flow process (DENTON, 2013).

Although the simulation of discrete events is widely applied in the simulation of health systems, agent-based modeling is growing, as it can better characterize the operation of complex systems, such as emergency departments. In the agent-based simulation, it is possible to model complexity from the behavior and interaction of individuals (CABRERA et al., 2011; DENTON, 2013).

A health system has many variables, and a single simulation method may not capture all the elements, or there will be no time to do so. Thus, it will not demonstrate the reality of the service. A hybrid method combining discrete event simulation and agent-based simulation may have the potential to more adequately represent the health environment and assist managers in decision-making and proposing improvements (DJANATLIEV; GERMAN, 2015; ABDELGHANY; ELTAWIL; ABDOU, 2016; BRAILSFORD et al., 2018).

Simulation methods can assist in the assessment, decision-making, and projection of improvements in urgent and emergency services. The theoretical background points to the existence of three growing simulation methods that can achieve the operational requirements necessary to assist in improvement projects. In this regard, the research question is presented: What is the most appropriate model to simulate the flow of patients in an emergency department?

1.2 Objectives

The general objective of this research is to assess the models of discrete events, agent-based, and hybrid simulation in the flow of patients in an emergency department. To achieve this, the specific objectives mentioned below are necessary:

1. Investigate the patient flow in emergency departments;
2. Investigate simulation and hybridization models in emergency departments;

3. Identify the main development and assessment criteria for patient flow and simulation models;
4. Compare the results of each simulation model; and
5. Build an orientation framework for the application of simulation methods in the emergency departments.

1.3 Justification

1.3.1 Socio-economic justifications

In health, the aging of the population, rising costs and scarcity of resources are motivators for more efficient management (THUEMMLER; BAI, 2017; MASSUDA et al., 2018). Current health systems and care models fail to meet future health demands (CURRY, 2005).

In Brazil, since 1988, there has been a universal health system known as SUS that guarantees access to health care for all Brazilians. However, SUS is in constant development, facing several challenges both in the care model, and in the financial and political structure (PAIM et al., 2011). It is easy to highlight public health problems by observing the queues at health units (COSTA, 2017).

In the private services market, there is a difference in their quality and availability. However, one of the most problematic services in both public and private sectors is the emergency department (COSTA, 2017; RECH et al., 2018). Waiting time is one of the major complaints of patients in emergency services. Long waiting times impact and are impacted by the demand for medical care (SILVA et al., 2016; RECH et al., 2018). The demand for patients seeking emergency departments is greater than it should be since more than half of these visits are not urgent. Patients seek these units because they are still the most available and effective services (ACOSTA; LIMA, 2015; RECH et al., 2018).

The emergency team's perceptions of the causes of the patients' long waiting time may not reflect the real situations, and this may lead to a misunderstanding in the allocation of resources to mitigate delays (CHAN; ARENDTS; WONG, 2008). It is necessary to evaluate the processes and find solutions to reduce the length of stay in the system, the patients' waiting times and increase the efficiency of resources (CABRERA et al., 2011; OH et al., 2016).

Simulation models may be suitable for solving problems in emergency departments. They serve as a timely accurate tool to assist health managers in optimizing the resources in a complex system with constant, inevitable, changes (ABO-HAMAD; ARISHA, 2013; OH et al., 2016). From quantitative and qualitative data, health managers can apply simulation to assess current performance and identify improvements, predict the impact of changes in hypothetical scenarios, and optimize flow and resources (OH et al., 2016; ZHANG, 2018). However, health managers still do not use these tools with the same intensity as the manufacturing and military sectors (NASEER; ELDABI; YOUNG, 2010).

The flow of emergency department processes can be modeled from the simulation of discrete events. The behavior of patients and interaction among patients, doctors and technical staff can be modeled based on Agent-based Simulation. Both methods are important, but individually may not be enough to demonstrate the reality of the emergency department, which has both service flows and a lot of interaction among agents (DJANATLIEV; GERMAN, 2015; BRAILSFORD et al., 2018).

Therefore, a hybrid simulation strategy, combining the two methods, may be the most appropriate considering the levels of abstraction necessary to identify and solve the problem (DJANATLIEV; GERMAN, 2015). In this context, it is intended to assess which simulation model is most suitable to meet operational needs, and to design improvements in an emergency department.

1.3.2 Theoretical justifications

Simulation studies in emergency departments were applied from the management perspective of the emergency department, medical decision-making, patient behavior, unit processes and performance, resource capacity and workforce planning (SALMON et al., 2018). The choice between discrete event simulation and agent-based simulation to assess the performance of emergency services depends on the requirements of the problem and not the modeler's knowledge of the applied method (SIEBERS et al., 2010; BORSHCHEV, 2013).

In the simulation of discrete events (DES), few models or studies treat entities and their active behavior as the central focus (SIEBERS et al., 2010). Most DES studies focus on problem-solving and specific units (GÜNAL; PIDD, 2010). Many projects are of academic origin and focus on analyzing capacity, processes and workforce at the operational level (SALMON et al., 2018). They, in turn, generate very similar works and make little progress in the simulation literature (ZHANG, 2018).

Agent-based simulation (ABS) can model real systems at a level of complexity that is not so common in DES (CABRERA et al., 2011). For simulation of the emergency service, agent-based modeling can contribute, due to its level of individual detail, as it is agent-based simulation involved in the system, such as, doctors, nurses, receptionists and patients (CABRERA et al., 2011; DJANATLIEV; GERMAN, 2015; MACAL, 2016). We still need to expand ABS knowledge to develop more effective models that can be used in practice to generate important information and support the analysis of results (MACAL, 2016).

A single simulation method may not capture all the characteristics and complexities of a system, and may lead to invalid assumptions or oversimplifications (BRAILSFORD et al., 2018). In this way, the application of combined modeling can be the way forward to solve the problems of behavioral operational research in the service industry (SIEBERS et al., 2010). For this, it is necessary to understand how each method can be used effectively with other simulation techniques so that each technique solves part of the problem (DJANATLIEV; GERMAN, 2015; MACAL, 2016). The use of hybrid modeling is emerging to expand the analysis in terms of strategic scope, and is applied in organizations (SALMON et al., 2018). A hybrid model using the DES and ABS methods can be better represented in an emergency department, as it uses DES that can represent the general system and ABS only for human behavior, thus unifying the positive points of each (ABDELGHANY; ELTAWIL; ABDOU, 2016).

There are already tools for comparison and selection of modeling and simulation methods that support health managers. However, these studies do not capture the complexity faced when applying the simulation to real problems, suggesting development of a better categorization of problems, the inputs required and the expected outputs in each method (JUN et al., 2011).

Despite the importance of the topic, there are few research papers containing an evaluation of which simulation method is most suitable for simulating an emergency department. Even more important, few consider the hybrid method with the combination of DES and ABS in the same model. Starting from the theoretical background, where the most current studies were assessed, this research aims to help guide which method is the most suitable for emergency department simulation, taking into consideration its advantages and disadvantages of using discrete event simulation, whether agent-based or a hybrid combining the two.

1.4 Delimitations

For this study, a discrete event simulation, agent-based simulation and hybrid simulation are developed, combining the two referred methods, considering that they are methods that evaluate the operation more appropriately. The study is restricted to these three simulation methods, not extending the study to other methods such as system dynamics. The literature description of other simulation methods is only to elucidate the history of the topic.

The study environment is an emergency department of a private health unit in Rio Grande do Sul State, Brazil. This unit has had its assistance process digitalized through an electronic medical record system since 2014. It provided an opportunity to collect electronic data.

The research uses the service database of this unit in 2018. The simulation models were focused on the emergency process. However, the steps and agents of the imaging examination center and the details of the procedures in the observation unit were not modeled due to the number of variables and limitations in the simulation software.

Receptionists, triage nurses, doctors, nurses and nursing technicians were modeled. Other agents were not considered, such as laboratory technicians, cleaning assistants and patient companions. The three simulation methods are applied in the same software, Anylogic 8, version Personal Learning Edition 8.4.0, given its opportunity to integrate different methods in the same model.

Studies from other health units were not conducted. The focus of the study did not propose operational improvements for the emergency department process, just as the experiments generated in the simulation environment were not applied in the real process.

1.5 Work structure

The study is organized in five chapters. Following this Introduction, Chapter 2 addresses the methodological procedures, the working method detailing the stages of the research development. Chapter 3 presents the theoretical framework covering the concepts of the emergency department, discrete event simulation, agent-based simulation, hybrid simulation, and the categories and evaluation criteria for the simulation, detailing the main inputs and outputs.

Chapter 4 describes the study environment, the conceptual model, the computational models, the comparison, analysis and discussion of the results, presenting the orientation framework. In Chapter 5, the last, final remarks, limitations and suggestions for future work are made.

2 METHODOLOGY

This section presents the methodological procedures for structuring this work, describing the basis of the research method and the details of the working method used to make the study operational.

2.1 Approach and type of research

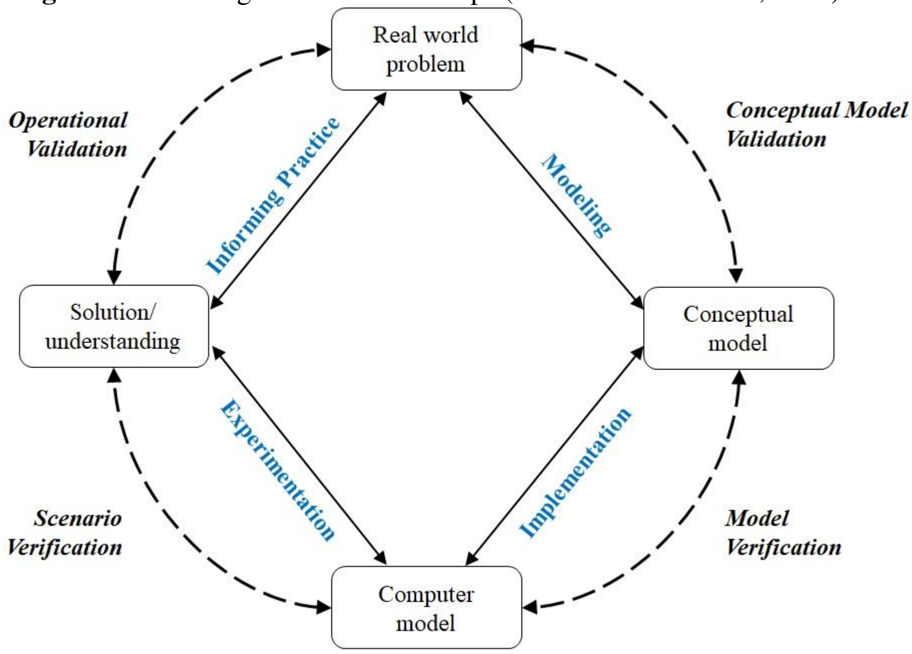
The method systematically organizes the activities and information, establishing a roadmap to be followed, to produce valid true knowledge (MARCONI; LAKATOS, 2017). This study is an exploratory research with a deductive approach of an applied nature. As a research method, it uses simulation. Simulation models are used to analyze complex systems imitating the operations of the real system over time (MIGUEL et al., 2012). Modeling and simulation are a way of systematizing the decision-making process, identifying problems and defining improvement strategies without interrupting the routine (MIGUEL et al., 2012; ABO-HAMAD; ARISHA, 2013; YOUSEFI; FERREIRA, 2017).

According to Will M. Bertrand e Fransoo (2002), modeling can be classified into two categories of research, axiomatic and empirical. Axiomatic research can be further classified as descriptive, which aims to understand the modeled process and the normative that aims to develop solutions to improve the results of the model and its problem. Empirical research is classified as descriptive, which creates a model to explain the causal relationships of real and normative processes that focus on creating a model to improve the current situation (WILL M. BERTRAND; FRANSOO, 2002). The work in question is characterized as empirical normative research that aims to evaluate the application of simulation methods in an emergency service.

2.2 Methodological Procedures

To model and simulate the emergency department, in this study, the simulation of discrete events, the agent-based simulation and the hybrid simulation combining DES and ABS are used. The work is based on the model developed by Sargent (2005) and adapted by Brailsford et al. (2018), represented by Figure 1.

Figure 1: Modeling and simulation steps (BRAILSFORD et al., 2018)



The Brailsford et al. (2018) framework, shown in the Figure 1, describes four steps.

1. The first seeks to identify the client's real problem and to solve it;

2. The second seeks to create the conceptual model, this being an abstraction from the real model that supports the researcher in defining the input, output, assumptions and simplifications variables (WILL M. BERTRAND; FRANSOO, 2002; ROBINSON, 2008);

3. The third develops the computational model, an important step since the model needs to allow the integration of simulation methods (in this DES and ABS research);

4. The fourth, solution and understanding, evaluates the results of the simulation, which may just confirm a conceptual model, or lead to a proposal for a potential real-world solution or to actually being implemented.

Among the stages of the real problem, the conceptual model and the computational model lies the process of validation and verification of the models, which can be based on statistical techniques or by means of interviews with specialists, the latter being a practice that increases confidence in the model (BRAILSFORD et al., 2018). The validation of the conceptual model assesses whether the model is consistent with the proposed simulation. The verification assesses whether the programming of the computational model is satisfactory, and whether the model conforms to the specifications (SARGENT, 2005).

Between the computational model and the solution to the problem, there is an experimentation stage verifying different scenarios. Finally, before implementation, it is necessary to validate the solution operationally, when this is the case. Operational validation assesses whether the behavior of the results has sufficient accuracy in relation to the intended model (SARGENT, 2005).

Brailsford et al. (2018), suggests three types of simulation studies: (1) models built for specific applications; (2) model structure that can be used by other modelers, illustrated in a real case; and (3) theoretical studies on modeling. This research will develop a model for a specific application and generate knowledge about simulation strategies for an emergency department.

The general objective of this research is to assess the models of discrete events, agent-based, and hybrid simulation in the flow of patients in an emergency department in a health unit.

The software used for the simulation is Anylogic, which, according to Djanatliev e German (2015); Alvarado, Lawley e Li (2016) and Brailsford et al. (2018)supports the development of hybrid models. The model modules are connected, which facilitates the model's construction phase (ABO-HAMAD; ARISHA, 2013).

The work method for this research is summarized in Figure 2.

The steps of the working method shown in Figure 2 are detailed below.

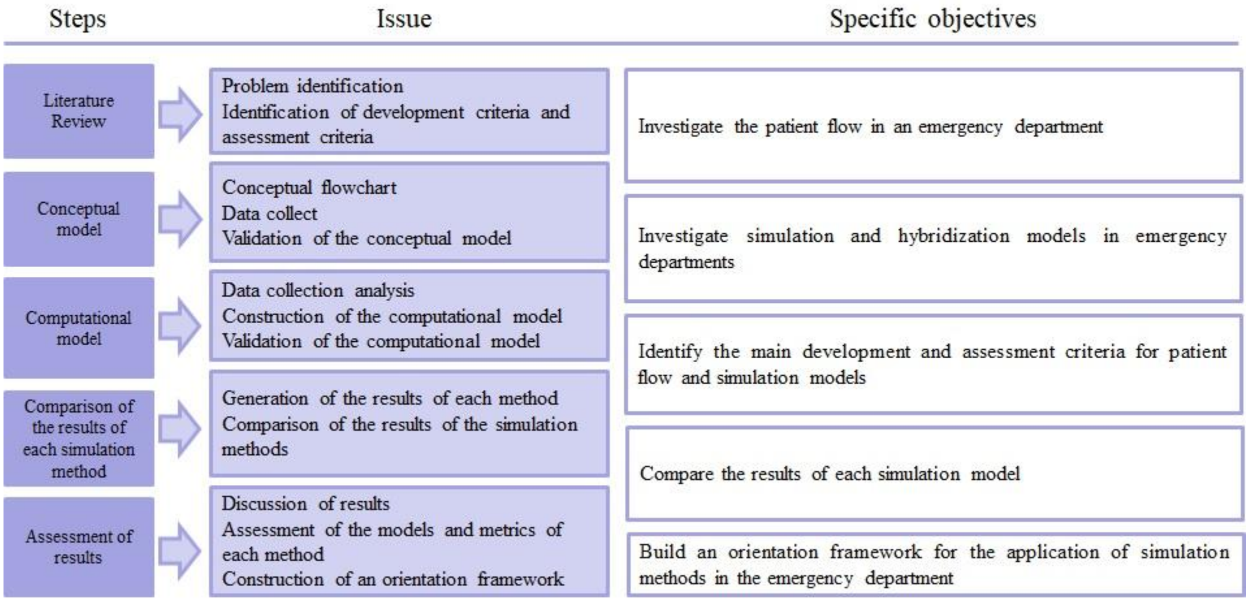
Step 1: Theoretical Background

Three searches were conducted in the Scopus database. All the selected papers are in the English language. The first search had the objective of identifying the studies of simulation of discrete events in emergency departments. The terms used were: "Emergency Department" AND "Discrete Events" AND "simulation" OR "modeling" OR "modelling", from 2015 until March 2020.

The second search found studies focused on agent-based simulation, the terms "Emergency Department" AND "Agent-Based" AND "simulation" OR "modeling" OR "modelling" were used.

The third search identified the hybrid simulation papers in emergency departments that used the combination of discrete-event simulation and agent-based simulation. The terms are "Emergency Department" AND "Agent-based" AND "Discrete Events" AND "simulation"

Figure 2: Steps of methodological procedures



OR "modeling" OR "modelling".

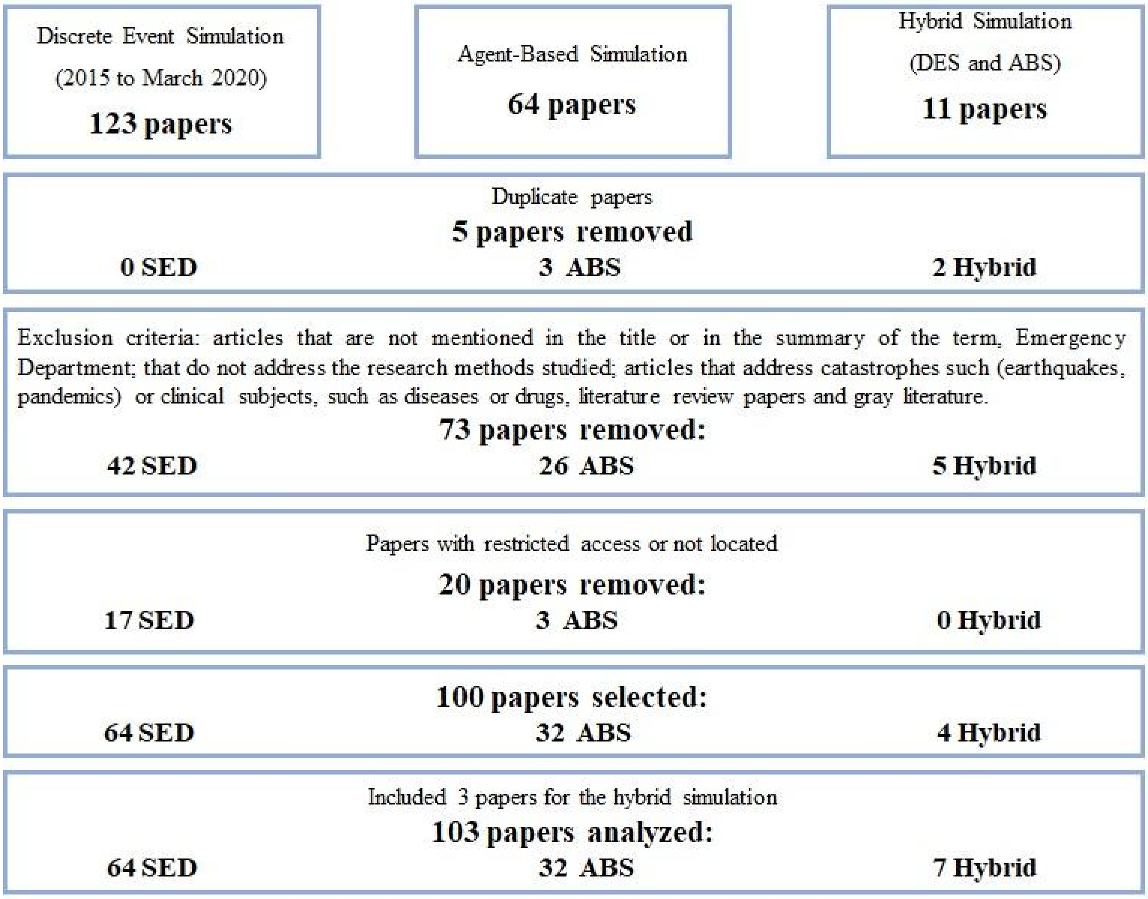
In total, 198 papers were found. Figure 3 summarizes the research steps. The exclusion criteria were the same for the three searches. The papers removed were: 5 duplicates; papers that did not mention the term Emergency Department in the title or abstract; that did not address the simulation methods searched; papers that addressed catastrophes (earthquakes, pandemics) or clinical subjects, such as specific diseases or infections, as well as literature review papers and gray literature.

The definition of gray literature includes scientific bulletins, reports, working papers, theses, government documents, bulletins, brochures, conference proceedings and other publications distributed free of charge, available upon subscription (WEINTRAUB, 2000).

All abstracts were reviewed using the exclusion criteria mentioned. 73 studies were removed: 42 from DES, 26 from ABS and 5 from hybrids. A total of 120 papers remained: 81 DES, 35 ABS and 4 Hybrids. During the reading, 20 more papers that had restricted access or were not found, were removed, 17 of them from DES and 3 from ABS. In order to complement the analysis of the studies in hybrid simulation, 3 papers were added, two on specific ambulance services and one on the radiology center.

The papers were analyzed and classified according to their simulation method, applied categories (detailed in the item below), inputs needed for the simulation, outputs extracted from the simulation. Specifically for the agent-based simulation method, the modeled agents

Figure 3: Theoretical background steps



were also identified. For the hybrid simulation method, it was highlighted which steps were modeled with DES and which with ABS.

Application categories

The simulations in emergency departments have a focus, whether to analyze, investigate, solve or provide information. Salmon et al. (2018) in their literature review, proposed classification of emergency department simulation research into six application categories. Sometimes the papers can be classified into more than one category:

- Managerial perspective;
- Medical decision-making;
- Patient behavior;

- Process and performance;
- Resource and capacity;
- Workforce planning.

The Management Perspective includes the entire accountability network, remuneration models, financial aspects, cost-benefit analysis, risk management and evaluation of new services. Medical Decision-Making is very influential in emergency departments, so simulations that involve physician interaction with patients, ordering diagnostic tests, decisions such as admission or patient discharge, new technologies or protocols that influence the medical decision are classified in this category (SALMON et al., 2018).

The Patient Behavior represents the individual decisions made, whether at the moment of choosing to leave without being seen, being under the influence of drugs or alcohol, or simply not accepting treatment. The Process and Performance category, on the other hand, focuses on modeling flows and processes to streamline services, increasing efficiency based on protocols, and improving time targets (SALMON et al., 2018).

The Resource and Capacity category includes models that assess non-human resources, such as the bed capacity or quantity of equipment. These analyses allow decision-makers to plan increases or reductions in the capacity and scheduling. The last category, Workforce Planning, focuses on team management, composition and quantity of human resources needed for emergency department efficiency. It also addresses shift management and the experience of employees in service quality practices (SALMON et al., 2018).

Step 2: Conceptual model

In the conceptual model, a flowchart of the emergency process of a health unit was constructed. For development of the model, the models described by Wang et al. (2015) and Yousefi e Ferreira (2017) were analyzed. These consisted of the steps of registration, screening (triage), exams, medical care, hospitalization in an intermediate bed and treatment, and the patient may be discharged at any time.

The information related to the study unit process was collected from direct observation of the service flow, from qualitative data described in internal documents stored in the company's quality management system. The stages of the process are: a) ticket number creation; b) risk screening (triage); c) patient registration; d) medical care; e) referral of conduct (discharge, observation or diagnostic examination); and f) discharge.

With the observations and patient records, it was possible to build the conceptual model. The model was validated by the Health Unit Administrator, responsible for managing the emergency unit under study, the demand, planning and allocation of resources for the unit, and who also has a relationship and direct control over all the teams in the process.

Data collection

Data collection took place within the organization by the researcher who works there. Access to information was authorized by: the manager responsible for all the company's care units; the Unit Administrator responsible for the management of the unit under study; and the Risk and Information Security Co-ordinator.

Three types of data were collected:

1. Qualitative data: access to internal quality management system documents was provided by the company. The main document consulted was the so-called "Emergency Care Process", which contains a description of the functioning of the unit studied.

2. Observational data: in-person observations were conducted of the stages of the service flow in the care unit studied. The observations were made during the morning and afternoon shifts in October 2019, lasting two hours each.

3. Quantitative data:

   - Data were collected from the institution's electronic medical records and hospital information system database. The data obtained were: dates and times of: the ticket number creation; the screening (triage); the registration; the medical care; the referral for observation; the discharge. Also, data on the type of care and degree of risk were obtained, which are necessary to define the prioritization of visits;

   - Human resources data were collected, considering the number of doctors and staff per shift.

Data from one year of service were collected, 78,124 records, corresponding to the period from 01/01/2018 to 12/31/2018. The quantitative data collected from the hospital information system needed, as stated by Alvarado, Lawley e Li (2016), to be reviewed, as the data was inaccurate or with unrecorded steps taken from the sample so as not to impair the accuracy of the information needed to enter the simulation.

Step 3: Computational model

By structuring the flowchart of the emergency department at the conceptual model stage, it is possible to identify the stages that will be built in the computational model. Also, with the quantitative data collected, the quantity of resources, the work shifts, the statistics on patient entry, the degree of risk, and the length of service at each stage, are determined. The collected data were analyzed and prepared to be included in the computational model. Data from 30 days of operation, 24 hours a day, were analyzed statistically to find the adherence curve of the data set.

Four simulation models were developed. One used only the discrete event simulation method, and another the agent-based simulation method. In addition, there were two hybrid models: the first modeling patients in ABS and the technical resources in DES, and the second modeling patients in DES and the technical resources in ABS.

For all the models, 2D and 3D animations were created allowing visualization of the patient service flow in a plan of the health unit during the simulation. This practice mainly helps managers to identify bottlenecks in the process, in addition to facilitating acceptance and understanding by the stakeholders not used to simulation.

The construction logic of each computational model is detailed in subsections 4.2.2, 4.2.3, 4.2.4 and 4.2.5. For each method, the modeling steps, the techniques to demonstrate patient entry, the quantity of resources, the patient's path through the unit, and, mainly, the way of integrating and communicating among the methods, are explained.

After creating the logic of the computational models, a dashboard screen was developed inside each simulator to monitor the results indicators. These indicators show the patient's length of stay, the number of patients entering and leaving, the waiting time and the time for each stage of patient care, as well as the use of resources, as suggested by Abo-Hamad e Arisha (2013).

The computational models undergo a 30-day warm-up period and then are simulated for another 30 days. In the end, the results of each method are statistically validated with the data from the real system. The statistical validation compared the patient's length of stay indicators, number of patients, time of activity and waiting for triage stages, registration and to see the doctor with the real data.

When identifying that most of the real data were within the confidence intervals, mainly arrival rate and length of stay, the validated process in each method was considered. Finally presented to the Health Unit Administrator to give a final opinion of the results and the visual flow of the emergency department, based on a systemic view of the process.

Simulation software

AnyLogic 8 Personal Learning Edition software version 8.4.0 was used to develop the computational models. This software was chosen primarily because it is one of the best tools that allows individual and integrated development of DES and ABS methods, as emphasized by Djanatliev e German (2015); Alvarado, Lawley e Li (2016) e Brailsford et al. (2018).

The software also has a graphical interface that facilitates its use, although, for ABS and hybrid models, knowledge of Java programming logic is necessary. The simulation models were developed and run on a computer with an Intel Core i7 7th gen. processor, 8GB of RAM and 2TB of ROM, using the Windows 10 operating system.

Step 4: Comparison of the results of each simulation model

After the computational models had been created and validated for the real system, the results of the simulation of each method were presented and compared statistically. To evaluate the models, each method was simulated 15 times with a warm-up period of 30 days.

The results are tabulated for each method at 16 points:

- Arrival;
- Wait for screening (triage);
- Time for screening (triage);
- Wait for registration;
- Time for registration;
- Wait to see the clinical doctor;
- Time seeing the clinical doctor;
- Wait to see the pediatric doctor;
- Time seeing the pediatric doctor;
- Wait to see the cardiologist;
- Time seeing the cardiologist;
- Wait to see the traumatologist;

- Time seeing the traumatologist;
- Time of observation in the chair (seated);
- Time of observation in the bed;
- Lenght of stay.

The average of each step, the standard error, the lower and upper limits were calculated, and the results evaluated within the upper and lower confidence intervals. The time to run the simulation in each method was also recorded and compared. This information is important to identify the strengths, the limitations of each method, and to which applications each method is best applied.

Step 5: Assessment of results

With the results identified and compared among the four simulation methods, the development of each method is assessed using the criteria of time, money, knowledge and need for data, as described by Naseer, Eldabi e Young (2010) and applied by Jun et al. (2011).

After each method had been compared and assessed in relation to time, money, knowledge and data, this information was analyzed together with the results identified in the theoretical background, and with the development and results of the models. An orientation framework was built to show the categories of possible simulation and which method is most suitable for application in an emergency department, depending on the type of approach to the problem and the proposed solution, as well as to explain the resource needs, and the inputs and outputs for each.

The study was then concluded with an assessment of the emergency department simulation models using each of the methods presented, explaining their advantages and disadvantages. It assists health managers and researchers in choosing the most appropriate simulation model to be applied in emergency departments. The next chapter presents the theoretical background used to support this study.

3 THEORETICAL BACKGROUND

This chapter presents the theoretical framework to ensure the quality and timeliness of the study. Simulation studies are important, as they serve as a tool to help health managers to optimize resources in a complex system with constant, and inevitable, changes like emergency departments (ABO-HAMAD; ARISHA, 2013).

3.1 Emergency department

The Brazilian health system involves a complex network of public and private service providers. It consists of three subsectors: (I) the Unified Health System (SUS), a public sector financed by the federal, state and municipal governments; (II) the private sector, making up for-profit and non-profit institutions financed with public and private funds; (III) the private health insurance sector, forming the extensive network of health insurance and tax subsidies (PAIM et al., 2011).

SUS, established in 1988, guaranteed the right to health for the entire population, with its principles being the universal right to health with equity, integrity, decentralized management and community participation (PAIM et al., 2011; RECH et al., 2018). Universal health systems are considered to be the ones that should best respond to the needs of the population, but underfunding brings several challenges to this system, compromising its resolution (MIRANDA; MENDES; SILVA, 2017). The main challenges of SUS are structural with gaps in organization and governance, low financing, lack of human and material resources. These difficulties, political crises, and an aging population weaken the public health system and cause regional disparities in access to services and results (MASSUDA et al., 2018).

The evidence of Brazilian public health problems is perceived when observing the waiting lines and the unassisted population in the health area. Government failures and deregulation bring about the existence of a fragmented service and the existence of a market dominated by the private sector, mainly by health plans and insurance financed by families or companies. The private market's differential is the quality and availability of specialized hospital, outpatient, and diagnostic services exclusive to paying customers. Making private health expenditures denominate one-third of national health expenditures (COSTA; VAITSMAN, 2014; COSTA, 2017).

One of the most problematic services in the Brazilian health system is the network of emergency services. The increase in demand and the insufficient structure creates overload and dissatisfaction for some users. Emergency services must be structured considering: the epidemiological profile of patients, existing resources, location, access, the most prevalent pathologies, and operational and technical capacity (RECH et al., 2018).

Regardless of whether they are public or private, emergency services in Brazil are comprised of 24-hour service, 7 days a week. The patient's flow usually has the steps of registration, triage, exams, medical care, hospitalization in an intermediate bed, and treatment, and the patient can be discharged at any time (WANG et al., 2015; YOUSEFI; FERREIRA, 2017).

The main indicators for measuring flow are: the number of patients who leave without being seen by a doctor; the average waiting time to be triage; the average time to be seen by a doctor and the length of stay in the unit (YOUSEFI; FERREIRA, 2017). Most of the time, these services have a high rate of variability, overcrowding and greater demand than the capacity of installed resources, generate excessive waiting time impacting the quality of care and patient safety (TAYLOR; NAYAK, 2012; VERMEULEN et al., 2014; VOSE et al., 2014).

Overcrowding in emergency departments is considered a global problem and it is defined as the condition for an emergency department to have difficulties performing its assessment and treatment functions, due to the excessive number of patients and physicians and resource capacity limited (YARMOHAMMADIAN et al., 2017). The main complaints refer to unresolved demands, long waiting times, and the service provided. The long waiting time for medical care impacts the overcrowding of the emergency services (SILVA et al., 2016; RECH et al., 2018).

For Chan, Arendts e Wong (2008); Yarmohammadian et al. (2017), the main causes for overcrowding and delays in the flow of care are:

- Increased service complexity;
- Increase in the number of visits;
- Increase in hospitalizations;
- Delay to support and diagnostic services;
- Delay to see specialists doctors;
- Lack of physical area and absence of beds;
- Increased filling of medical records and paper records;
- Language and cultural barriers;
- Difficulty in managing the flow.

Another causal factor and one of the main points of discussion is the number of patients who could seek a primary care unit instead of an emergency unit. Approximately 60 % of patients could be treated on an outpatient basis, although, the worsening of diseases already installed makes the patient seek an emergency care unit, as they are more agile and resolving care services to these situations (ACOSTA; LIMA, 2015; SILVA et al., 2016; RECH et al., 2018). Health care is vital. The emergency departments have a high responsibility in the health system, being the most critical unit in a hospital. It is necessary to have rational methods for solving problems. Simulation is a method that provides operational, tactical and strategic analysis for decision-makers (GUL; GUNERI, 2015).

3.2 Modeling and simulation in emergency departments

The modeling includes a set of controlled variables that are modified in a specific model demonstrating causal and quantitative relationships (WILL M. BERTRAND; FRANSOO, 2002). A model is a simplified representation of reality that demonstrates an understanding of the problem studied, which needs to capture all the necessary elements and be simple, enabling treatment by analysis methods (MIGUEL et al., 2012).

Quantitative models are described mathematically or computationally and use analytical and experimental techniques to identify the results of different situations (MIGUEL et al., 2012). The essence of operations management based on quantitative models was built from Taylor's scientific management, through observations, measurements and analysis of real operational processes aimed at redesigning processes to improve inventory control, scheduling sequencing, control of quality and maintenance (WILL M. BERTRAND; FRANSOO, 2002).

From the causal relationship among variables and the development of models that represent reality, it is possible to create models to predict the future state of processes and assist in decision making (WILL M. BERTRAND; FRANSOO, 2002). With the theoretical evolution in mathematics and statistics and with new technologies, it is possible to increase the complexity of the models, consolidating operational research as an important instrument in decision making (MIGUEL et al., 2012).

Operational research is a toolbox of methods, and it is necessary to evaluate which method is most suitable for a given problem (BRAILSFORD et al., 2018). In operational research models, simulation is applied to analyze complex systems. It consists of imitating real systems that evolve and can be static or dynamic, dynamic ones analyze continuous and discrete systems (MIGUEL et al., 2012).

For Brailsford et al. (2018), in operational research, modeling and simulation is the process of problem definition, method selection, conceptual modeling, computational implementation, data collection, parameterization, verification and validation, development of scenarios to be tested, experimentation, analysis and presentation results and use those results to inform a real-world decision.

Sargent (2005), describes that verification and validation are important steps to ensure the accuracy of the simulation model. They can be subjective and objective, usually using a combination of techniques, from animation validation evaluating the operation's behavior during the simulation to statistical tests with hypothesis tests or confidence intervals.

Borshchev (2013), describes six advantages of simulation models.

1. simulation models analyze systems and find solutions that other methods may not achieve;
2. after defining the appropriate level of abstraction, the simulation process tends to be more direct than other models;
3. the simulation model structure usually reflects the real structure and, from visual languages, it becomes easier to communicate the model to other people;
4. ease of statistically measuring any value at any stage of the process;
5. using the animation of the system's behavior to support improvements and checks;
6. simulation models can be more convincing than Excel spreadsheets in order to present a new model proposal.

An organizational system is composed of several subsystems interrelated for a given objective and share elements such as inputs, processes and, outputs. Complex systems involve many dynamic elements and different levels of emotion that interact in a disordered way and that contribute to the structure of a whole (YOLLES, 1999; LADYMAN; LAMBERT; WIESNER, 2013).

In the health area, simulation is not yet used to the same extent as other industries, such as manufacturing and military (BOUZON NAGEM ASSAD; SPIEGEL, 2020). Simulation modeling is applied in several areas and processes. In the health area, due to the complexity of its systems, simulation is an important tool in improvement projects (ALVARADO; LAWLEY; LI, 2016). In health, simulation can evaluate scenarios, compare, analyze hypotheses, analyze sensitivity and optimize processes.

There are several challenges in developing health simulation models, as in these environments it is necessary to consider privacy, security and data quality, especially of patients, safe access to facilities, national regulations and also the collaboration of multidisciplinary stakeholders (ALVARADO; LAWLEY; LI, 2016). Simulation modeling is used in emergency departments, scheduling patients, planning beds, new facilities, expanding a hospital and other hospital services and operations (GUL; GUNERI, 2015).

Studies from modeling in emergency departments have been underway since the 1980s. The process and the similar layout in several countries, as well as waiting and processing time problems have made the emergency department one of the most modeled systems in operational research in health (SALMON et al., 2018). Because emergency departments have more autonomous steps than other hospital units, implementing improvement actions is easier to demonstrate (GÜNAL; PIDD, 2010).

Emergency departments have different levels of urgency, ranging from immediate and invasive life-saving interventions to treatments for minor injuries and discomfort. Usually, these patients go through the same processes and resources within the hospital, creating a great challenge for management and simulation (SALMON et al., 2018).

The importance and scale of the emergency department's services within a hospital system and the complexity of the processes and their decisions justify the need for interdisciplinary decision support methods demonstrating to managers the best possible solutions. The modeling and simulation approaches allow the application of tools to assist in this process (SALMON et al., 2018).

There are three main methods of health simulation and modeling: System Dynamics (SD), Discrete Event Simulation (DES), and Agent-Based Simulation (ABS). SD and DES are traditional in health simulation, SD is more used in strategic and political decisions, DES is better for assessing patient flows, processes, capacity and resource utilization, whereas ABS is emerging as a potential to analyze the interrelationships among health care participants. They are used in individual or population level analyzes (ABO-HAMAD; ARISHA, 2013; ALVARADO; LAWLEY; LI, 2016). DES is the most popular method, Salmon et al. (2018) in his systematic review identified 209 articles that report the use of the DES method, 25 that used ABS, 18 systems dynamics and only 13 with hybrid models such as DES / SD or DES / ABS.

The simulation of discrete events corresponds to events in which the variables change state instantly over time. Usually represented by complex flow diagrams (LAW, 2007).The system is modeled as a process through entities (BORSHCHEV, 2013). However, in this method, even when modeling individuals, their states are predefined at some stage of the process (DENTON, 2013). Entities represent customers, patients or documents, for example. The resources represent staffs, doctors, operators. The outputs normally obtained are resource utilization, time spent in a process step, queues, waiting time, bottlenecks, among others (BORSHCHEV, 2013).

For simulating the emergency service, agent-based modeling can be useful, as it analyzes complex systems based on modeling the behavior of individuals, the relationship among them, and the physical environment making it more realistic. However, it involves many assumptions at the individual level and their interactions and can become very complex (DENTON, 2013). The development of the ABS method is from the bottom up, modeling the statechart of an agent and its interaction with other agents. In this method, it is not necessary to have a process flow and its dependencies (BORSHCHEV, 2013).

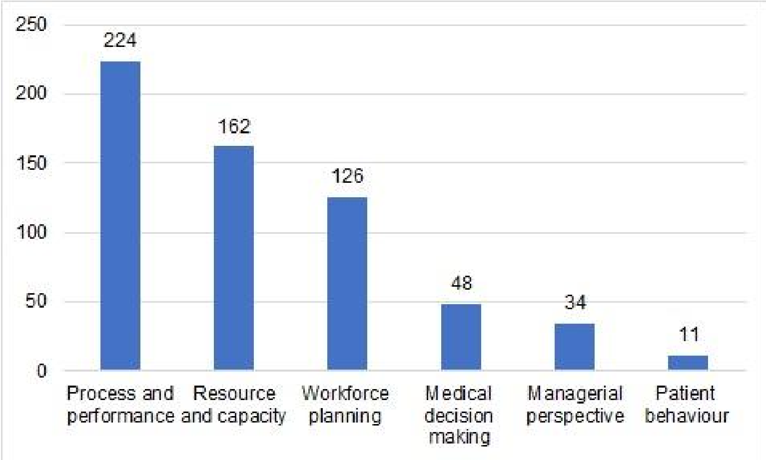
Determining the level of detail in the model can be difficult. A suggested solution is to use hybrid models incorporating an agent-based model and discrete event simulation, modeling both their interaction with other agents and an internal flow model, taking advantage of the strengths and overcoming the weaknesses of each method (DENTON, 2013; BRAILSFORD et al., 2018).

When modeling in just one method, possible alternative solutions are needed or some part of the scope will be left out. The structure of the model reflects the structure of the system being modeled at a certain level of abstraction. The choice of the method must consider the naturalness criterion, easy to understand and to explain (BORSHCHEV, 2013).

DES and ABS platforms vary from models, low level, developed using general programming language, and high level, in which specialized simulation platforms are used. Studies show that the most used software for simulating discrete events and agent-based are high-level simulation platforms.The main platforms for DES are Arena, Simul8, Promodel and Awesim software. For ABS they are Netlogo, Anylogic, Repast, Swarm and C ++, although even with software this method usually requires the incorporation of programming code (ALMAGOOSHI, 2015; ALVARADO; LAWLEY; LI, 2016).

Salmon et al. (2018) identified, as shown in Figure 4, simulation studies applied to the management perspective of the emergency department, medical decision making, patient behavior, unit processes and performance, resource capacity, and workforce planning. Hospitals no longer have resources or available, in which case it is necessary to use resources more efficiently.

Figure 4: Simulation application categories (SALMON et al., 2018)



Most simulation publications in emergency departments address operational problems, such as the daily flow of patients, although an emergency department operates within the broader context of a hospital (SALMON et al., 2018).

The choice of method will depend on the system to be modeled and the purpose of the simulation, although, it is often chosen by the modeler's knowledge (BORSHCHEV, 2013). The choice between discrete event simulation or agent-based simulation to assess the performance of an emergency department depends on the requirements of the problem and not on the knowledge of the modeler, that is, to identify the research question and then assess which is the best applicable method (SIEBERS et al., 2010).

Simulation is increasingly involving tactical and strategic levels, with emergency departments to remain efficient are becoming more dependent on adjunct systems such as hospital care, primary care and social assistance. For Salmon et al. (2018) researchers need to be able to identify those dependent models that improve service performance, to more strategic levels, hybrid simulation methods are on the rise. The subsections below clarify the DES, ABS and hybrid simulation methods and their application in emergency departments.

3.3 Discrete events simulation in emergency departments

The simulation of discrete events proves to be a good tool for modeling and improving health processes (JUN; JACOBSON; SWISHER, 1999). Health managers can apply DES to assess, based on quantitative information, current performance, and identify improvements, predict the impact of changes in hypothetical scenarios, optimize flow and resources (OH et al., 2016; ZHANG, 2018). DES is suitable for analyzing problems in emergency departments, where resources are scarce and patients arrive at irregular hours (JUN; JACOBSON; SWISHER, 1999).

DES has been widely used in modeling health systems for many years (GÜNAL; PIDD, 2010). Efforts to develop DES models have advanced since the late 1980s when Saunders et al. (1989) proposed a model to study the impact of resources on waiting times and throughput. The number of published articles has increased significantly since 2004 (GÜNAL; PIDD, 2010), after 2010 the number of publications on DES modeling in healthcare management increased again (ZHANG, 2018).

Zhang (2018) classified DES models into four main categories: health systems operation, disease progression modeling, triage modeling, and health behavior modeling. The papers with the highest publication are applied to the operational analysis of health systems and represent the proportion of (65 %) of all modeling studies over time, followed by the disease progression model (28 %) and triage (5 %), finally, are the papers that address health behavior modeling (2 %).

DES modeling is used to solve several operational problems, Zhang (2018), based on Lagergren, categorizes into six main operational research approaches: (1) patient scheduling (including scheduling appointments and discharge for outpatients and inpatients), (2) resource allocation, (3) planning and management capacity, (4) workforce scheduling, (5) system diagnostics and (6) evaluation of the effects of operational changes or reconfigurations.

One of the challenges of the simulation of discrete events considered the key to success by Günal e Pidd (2010), is to choose the appropriate level of details of the model, this will impact the time needed to develop the model, to collect the data and to convince stakeholders about the utility of the model. The greater the number of details, the more realistic the model, increasing the confidence of decision-makers, although, the collection and validation of data become more complex and time-consuming.

The lack of data generated in healthcare environments can impair modeling, as based on expert estimates or literature data, rather than actual observations, the accuracy of the model can be affected (ZHANG, 2018). These simulation models are usually based on historical data sources, or real-time data collected from the software. At the beginning of the century, the challenge was the availability of electronic data, currently with the advancement of technology, the availability of data has increased considerably, now the challenge is to obtain qualified electronic data, requiring data mining (ALMAGOOSHI, 2015).

In their review of the literature, Günal e Pidd (2010) criticize that most studies on DES focus on solving specific problems in individual units of the health system, such as demand problems in emergency departments, reducing waiting times in outpatient clinics and optimizing the use of hospital beds. Zhang (2018), demonstrates that more than 68% of the modeling papers of the health operating systems were concentrated on unique microsystems. Generating very similar works, making little progress in the simulation literature.

There are few generalizable publications, building the general theory, just as models are usually developed for specific hospitals, and it is not possible to reuse them in other hospitals (GÜNAL; PIDD, 2010; ZHANG, 2018). Another challenge is the lack of terminology, the same areas, processes and services may have very different names in the healthcare environment, hampering modeling and generalization (ZHANG, 2018).

Another issue, observed by Günal e Pidd (2010), is the simplification of a simulation model to just one unit, which can harm the holistic view of the problem. The modeling of a hospital as an entire system allows the identification of the links among the flows of patients, emergency departments, operating rooms, nurses on admission. As of 2010, the number of studies that model integrated and complex health systems has increased, but at a more abstract level, simulating only a sequence of essential activities among patient entry, stay and discharge (ZHANG, 2018).

To contribute to the study, 64 papers that meet the researched criteria for the simulation of discrete events were assessed. It is observed that the variation of authors is greater about the number of published on the methods of SBA and Hybrid.

Recently d'Etienne et al. (2020) developed a model to predict the patient's length of stay in the emergency department, after the triage stage and thus already refer long-term patients to the inpatient unit. The model was first applied in a simulation of discrete events showing satisfactory results.

Another study published in 2020 by Bouzon Nagem Assad e Spiegel (2020) describes an optimization and simulation approach seeking the best workforce configuration in four Brazilian emergency departments. After obtaining the parameters, the scenarios were applied to a DES model to assess the impacts of cost reduction and labor allocation.

De Boeck, Carmen e Vandaele (2019) assist medical decision-making by analyzing the suggestion of implementing policies to prioritize which patient needs to be evaluated first among new patients and patients admitted to an emergency department. The choice of patient prioritization has a different impact on the length of stay and the waiting time for patients.

Landa et al. (2018) developed a study, based on the simulation of discrete events, to assess the best configuration of bed management in an emergency department in Italy. From operational and tactical decisions, they were analyzed in the ED optimization.

Rachuba et al. (2018) analyzed, through a DES, the patients' length of stay and waiting time after the application of a discharge strategy by the radiologist right after the image was taken. Rachuba et al. (2016) also analyzed, through a DES, the patient's length of stay and the number of hospitalizations based on the application of a test to identify patients with acute myocardial infarction.

Goienetxea Uriarte et al. (2017) use discrete event simulation, simulation-based multi-objective optimization, and data mining techniques to investigate the optimal solutions for an emergency department in Sweden. The experiments improved the processing time by 52%. The authors further emphasized the need to involve hospital stakeholders in the study.

Hussein et al. (2017) integrated the Six Sigma methodology with DES to improve the performance of the emergency department by including an imaging technology and new digital X-ray equipment. Bal, Ceylan e Taçoğlu (2017) combined Lean and DES to improve the ED result, after the construction of a future value flow map the simulation proposals were applied in a simulation model.

Ahmad et al. (2017) developed a DES for hospitals in Malaysia to support resource allocation and assess the impact on patient stay and waiting time. Ahmad et al. (2015) created a hybrid simulation using DES to simulate the operation of the emergency department and Systems Dynamics to assess the interdependence of ED with other hospital units.

Finally, Oh et al. (2016), developed a decision support tool, based on a DES, for an emergency department in the United States. From the experimentation of scenarios with different levels of resources, a reduction of 30% in the patient's stay time was obtained. Oh et al. (2016), also developed a framework, Figure 5 for building the simulation.

Figure 5: Framework for simulation development (OH et al., 2016)

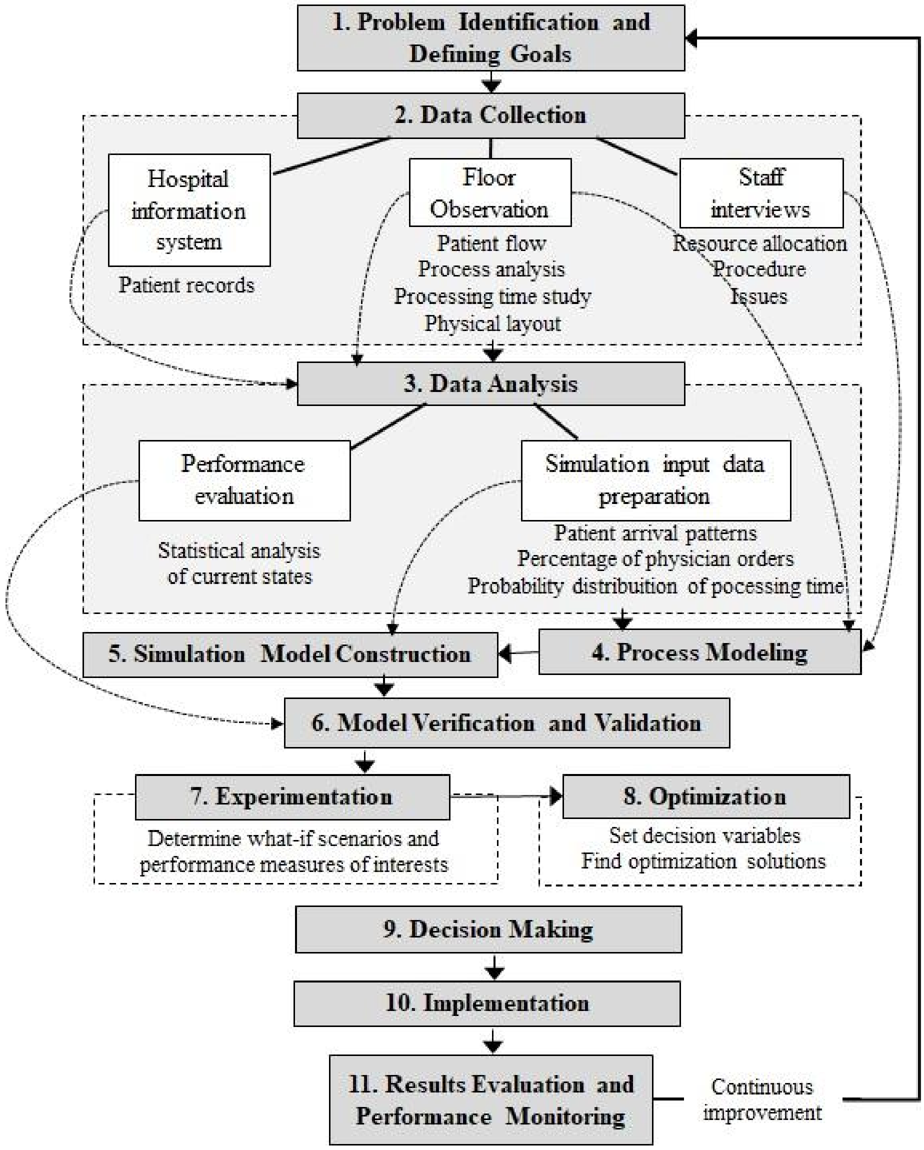


Figure 5 details the steps for building the simulation, starting with the identification of the problem and definition of the objectives. Afterward, the data is analyzed to design a process model to identify the sub-processes and the connections between patients and resources. This information is used as input for the development of the simulation model. After executing the model, it is necessary to check and validate the model. The evaluated model is used to experiment and optimize scenarios. Finally, the results support decision-making to implement or evaluate the results that feed the flow (OH et al., 2016).

Integrated DES modeling among different units can benefit health care management by analyzing different customers and suppliers, as well as the satisfaction of patients who, in their experience in the health system, go through this integrated system. DES modeling for problem-solving at the strategic level is practically non-existent, possibly because this technique is more operational for health care flow problems (ZHANG, 2018).

3.4 Agent-based simulation in emergency departments

Unlike DES, which is historically linked to operational research, agent-based simulation is associated with a large number of different disciplines, started to be discussed from the theory of complexity and the creation of the Santa Fé Institute in the 1990s (WALDROP, 1994), that brought together different experts to share knowledge and problems, resulting in several models that demonstrated how simple rules of interaction can lead to complex behaviors (SIEBERS et al., 2010).

Agent-based simulation facilitates understanding of the real world, as it represents and models individuals and their autonomous behaviors so that agents respond to the simulated environment (SIEBERS et al., 2010). The number and range of agent-based modeling and simulation (ABS) applications is steadily growing (SIEBERS et al., 2010; MACAL, 2016).

There is a discussion about the agent-based simulation that questions whether this method deserves due attention or is it just a disguised form of standard simulation methods that call ABS to simulate flows that a DES or SD could run (MACAL, 2016). Siebers et al. (2010), on the other hand, states that this method makes it possible to model real-world systems that were not possible or unusual by applying traditional modeling techniques, such as discrete and dynamic simulation of systems.

What is lacking in traditional simulation methods is the modeling of human behavior, its reactions, interactions in a way to predict or test interventions. These characteristics are the most important in ABS, as its modeling construct is the agent and its behaviors, which interfere in the actions and decisions themselves, in the actions of other agents and with the environment and process. It can even consider all the logical components of a DES model, and also explicitly model the complexity of individual actions (SIEBERS et al., 2010; MACAL, 2016).

Another difference of ABS compared to traditional simulation methods is the bottom-up approach, unlike the others that, in most cases, models from top to bottom. ABS becomes one of the main methods for simulating people, organizations and societies (MACAL, 2016) An ABS can be conceptualized in several ways, Macal (2016) presents four definitions of agent-based modeling and simulation:

1. Individual: agents in the model represented individually with different characteristics;

2. Autonomous: individual agents with autonomous internal behaviors, detect any condition that occurs within the model;
3. Interactive: autonomous agents interact with other agents and with the environment;
4. Adaptive: autonomous agents interact with other agents and the environment and change their behavior during the simulation, as agents learn, they encounter new situations.

Concept 1 represents the agent's ability to act independently during the simulation process, based on previously scripted behavior. Concept 2 demonstrates the reactive capacity of agents based on the state of the system at any time and to act without direction provided externally. The internal state of an agent is implemented as a subset of defined characteristics that are updated dynamically during the simulation at scheduled event times (MACAL, 2016).

Concept 3 is common in social simulation, as it models social interactions, in this type of model the computational complexity is greater, as it involves the coordination of agents. Concept 4 represents the ability of an agent to adapt and change his behavior by including new information in his internal state when faced with a new situation, or a situation of previous encounters, in which case more advanced algorithms are needed like machine learning or genetic programming (MACAL, 2016). An agent-based model is characterized by its internal properties, the Table 1 presents a summary of these characteristics.

Table 1: Types of agents (MACAL, 2016)

Agent definition / properties	**Individuality**	**Behavior**	**Interactions**	**Adaptability**	**Examples**
Individual ABS	Individual heterogeneous agents *	Prescribed, with script †	Limited	none	Traffic model that has agents moving between source and destination pairs according to a script
Autonomous ABS	Individual heterogeneous agents *	Dynamic, autonomous ‡	Limited	none	Model in which agents choose occupations and places to work, but do not interact with others
Interactive ABS	Individual heterogeneous agents *	Dynamic, autonomous ‡	Among other agents and the environment¶	none	Infectious disease model in which agents transmit and are infected through contact and respond to their disease state according to prescribed behaviors
Adaptive ABS	Individual heterogeneous agents *	Dynamic, autonomous ‡	Among other agents and the environment¶	Agents change behavior during the simulation	Care model in which agents modify their behaviors according to the state of their health

* Population agents have different characteristics.

† Agent behavior is provided exogenously and is not based on endogenous events during the simulation.

‡ The agent's behavior is endogenous based on the current state of the agent.

¶ Agent behaviors are based on the observed states and behaviors of other agents and the state of the environment.

The agents change behaviors during the simulation, the agents learn and / or the populations adjust their composition.

In Table 1 it is possible to distinguish the ABS approaches as to the type of model and its operation. Therefore, when developing an ABS it is important to understand the model and its agents as to their individuality, autonomy, interactivity and adaptability (MACAL, 2016). Siebers et al. (2010), guide to understand people and their behaviors through interviews and observations and, with this data, develop the agent-based model and evaluate their results.

Agent-based modeling is attractive because it offers the ability to model a population of heterogeneous agents (MACAL, 2016). ABS can be used, according to Siebers et al. (2010), when:

1. the objective is to model the behavior of individuals in a diverse population;
2. agents have relationships with other agents;
3. individual agents move behaviorally;
4. agents learn or adapt;
5. the agents engage in strategic behavior and anticipate the reactions of other agents when making their decisions;
6. agents cooperate, conspire or form organizations;
7. the past is not a predictor of the future;
8. scaling to arbitrary levels is important;
9. structural process change needs to be a result of the model, rather than an input to the model (for example, agents decide which process to go next).

Nowadays people are more used to using the simulation of discrete events and try to adapt them to all problems. As people use ABS, new problems that were previously not properly solved using DES will arise (SIEBERS et al., 2010).

Macal (2016) describes some challenges for the future of ABS:

- Increase the credibility and confidence of the models and their results, solving problems that justify the use of this method;
- Increasing transparency in the models, very complex models make it difficult to explain the results and replicate them;
- Expand ABS knowledge to develop more effective models. It is used to generate important information, analyze and explain its results;

- Increase the ease of using ABS tools and software.

Siebers et al. (2010), described that new modeling procedures are necessary for ABS challenges such as coding agent behaviors and validating the components of the behavioral model. Another challenge is to establish a method to represent the behavior of agents in a model and a method of analyzing data and statistics to extract significant information from the simulation results. Relating the behavior of agents at the micro-level with the result of systems at the macro-level (MACAL, 2016).

The emergency department is one of the most complex systems in the health system, consuming a large part of a hospital's budget, while patients complain about the unit's delay and capacity (TABOADA et al., 2011). However, more than half of these emergency services are non-urgent and can be treated in alternative health settings (CABRERA et al., 2011).

The activities of the emergency departments are not linear, there are variables such as time, day of the week, and season that impact demand, making resource planning difficult. The simulation of complex systems can assist in decision making. An effective technique is an Agent-Based Simulation (ABS), which allows for the addition of details in simulation experiments, enabling learning and the ability to control and modify individual behavior (TABOADA et al., 2011).

Agent-based simulation can model real-world systems at a level of complexity that is not so common in other modeling methods like DES, for example. ABS, in this case, assists in the characterization of complex systems such as emergency departments. The rules of the model are based on the agents involved in the system such as doctors, nurses, receptionists and patients. The behavior of the system is the result of the actions and interactions of these agents with the environment (CABRERA et al., 2011).

In the emergency departments, Cabrera et al. (2011), identified two types of agents. Active agents, represented by human actors who act on their own initiative as patients, assistance team, administrative team. Passive agents, represented by reactive services and systems such as infrastructure, information technology (IT) and laboratory and radiological diagnostic and complementary services.

Moore's state machines are used to represent the actions of each agent. This method considers variables that represent different states of individuals (patients, medical staff, among others) during the process. Agents receive variables as inputs and produce outputs that are modeled as a transition among states (WANG, 2009; TABOADA et al., 2011; CABRERA et al., 2011).

ABS papers applied in emergency departments to support the study were analyzed. 32 eligible papers were identified from 2008 to 2020. In Table 2 highlights the main agents modeled by the studies.

Table 2: ABS modeled agents

Agents	Amount
Doctors	32
Patients	26
Nurses	23
Triage nurses	22
Receptionists	21
Nursing technicians	8
Beds	4
Emergency Departments	2
Radiologists	2
Laboratory technician	2
Patient's companion	2
Assistance team	2
Queue manager / Controller / Bed manager / Operations center	2
Speaker	1
Diagnostic Center	1
Nurse triage	1
Laboratory tests	1
Contact Information	1
Diagnostic rooms	1
Information system	1
Pneumatic tube	1

As shown in Table 2 the most modeled agents are doctors, patients and nurses. The patient is the entity in which his behavior will affect the result and the quality of the process. Doctors and nurses, as well as triage nurses and receptionists, are the resources that most interact with patients, and their dimension and behavior influence the unit's performance.

The first paper located at the base is from 2008. In this research, patients, receptionists, triage nurses, doctors, nurses agents, and the beds themselves were considered in the modeling. The goal was to improve the time until medical care from adjustments in the medical schedule (JONES; EVANS, 2008).

Laskowski conducted four studies with other authors using agent modeling in emergency departments. The first study in 2009, Laskowski et al. (2009) conducted a study to gain insights into ABS techniques and queuing theory and evaluate them. Also in 2009, a study was started using ABS and RFID tools to simulate resource usage policies and patient behavior (LASKOWSKI; MUKHI, 2009).The survey was applied in 2010 as (LASKOWSKI et al., 2010). Finally, in 2011 Laskowski (2011) presents an integration between ABS with a genetic programming machine learning system creating a tool for making complex decisions.

Cabrera et al. developed a decision support system in an emergency department in Spain to optimize resources and improve waiting times based on a simulation using the variable's arrival time, agents, experience and cost. Following papers published by the research group, patient agents, receptionists, doctors and nurses were evaluated under certain economic and operational conditions (CABRERA et al., 2011, 2012a,b,c).

Taboada et al., In the same research group, developed research to evaluate the scheduling and admission strategies of patients in the Spanish emergency department. A decision support system was developed to allow the allocation of patients and resources in different locations according to the patient's severity level and unit demand, thus allowing a reduction in waiting time (TABOADA; CABRERA; LUQUE, 2011; TABOADA et al., 2012, 2013).

Liu et al. also in an emergency department in Spain, it demonstrated, from the publication of three papers, a generic ABS model that allows predicting the behavior of patients and resources such as receptionists, triage nurses, nurses, doctors, technicians and diagnostic imaging professionals. The created model allows calibration and statistical validation as real services (LIU et al., 2015, 2017a,b).

Yousefi e Ferreira (2017) developed a simulation model to help managers' decision making using a group of experts to make the resource allocation decision. In another study, Yousefi et al. (2018a) used ABS, machine learning, and generic algorithms to find the optimal allocation of resources and decrease the time spent in the Emergency Department. Yousefi et al. (2018b), simulated the behavior of patients and evaluated four strategies to improve the length of stay and decrease the rate of patients who leave without being seen by a doctor, the result was to develop a rapid care strategy for patients with little urgency. Finally, Yousefi e Yousefi (2019) presented a simulation-based on metamodels to improve resource allocation, the time until medical care, and also improve the computational time of the simulation.

In addition to modeling only resources, Moustaid, Richard e Meijer (2018) and Moustaid e Meijer (2019) simulated how the provision of information about waiting times in emergency departments in Stockholm city impacts the patient's behavior in choosing which unit to go to and its relationship with the wait time.

Table 3: Differences between DES and ABS, adapted from Siebers et al. (2010)

DES method	ABS method
Process-oriented (top-down modeling approach); The focus is on modeling the system in detail, not on entities	Based on the individual agent (bottom-up modeling approach); focus is on modeling the entities and interactions between them
Top-down modeling approach	Bottom-up modeling approach
One control line (centralized)	Each agent has its own control line (decentralized)
Passive entities, this is something that is done for the entities as they move through the system; intelligence (eg decision making) is modeled as part of the system	Active entities, that is, the entities themselves can take the initiative to do something; intelligence is represented within each entity
Queues are a key element	No queuing concept
Flow of entities through a system; macro behavior is modeled	No concept of flows; macro behavior is not modeled, it emerges from the micro decisions of individual agents
Input distributions are generally based on data collected / measured (objectives)	Input distributions are often based on theories or subjective data

Siebers et al. (2010), make a comparison of the two simulation methods, as shown in Table 3. They state that there are no true ABS models in operational research, but combined models between DES and ABS in which the process flow through the DES and then adds the active entities that are autonomous and behavioral from ABS.

Siebers et al. (2010) when evaluating Table 3 concludes that the simulation technique is linked to the perspective taken by the researcher (agent perspective or process perspective), which, in this way, defines which model to use. Finally, it states that the combined application of DES and ABS seems to be the way to solve problems in the service industry.

Abdelghany, Eltawil e Abdou (2016), also made a comparison between the DES and ABS models. Table 4 summarizes the identified capabilities and limitations.

Table 4: DES and ABS capabilities and limitations, adapted from Abdelghany e Eltawil (2014)

	Capabilities	Limitations
Discrete events	Queuing modeling facility Top-down modeling Focus on detailing the system flow	Does not observe indirect tasks related to the patient their interactions with the team Does not consider the side effects of the changes Does not model interactions among entities (patients, teams)
Agent-based	Bottom-up modeling Focus on entity modeling and their interactions	Do not observe queues and flows existing in the system Models take longer to develop, need more data and knowledge of decision-making rules

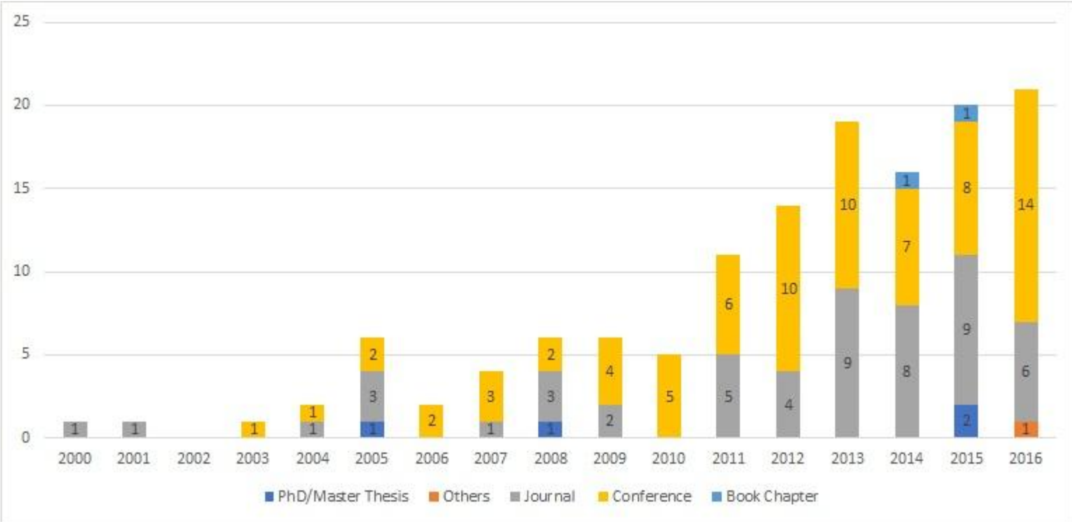
In Table 4 it is possible to evaluate the advantages and disadvantages of each model, which helps in choosing which method is the most suitable for simulation.

3.5 Hybrid simulation in emergency departments

Hybrid modeling and simulation are the combination of two or three simulation methods, usually combining discrete event simulation, agent-based simulation and/or system dynamics. Use modeling tools, integrating logical elements in a way that makes sense (HEATH et al., 2011; MACAL, 2016; BRAILSFORD et al., 2018).

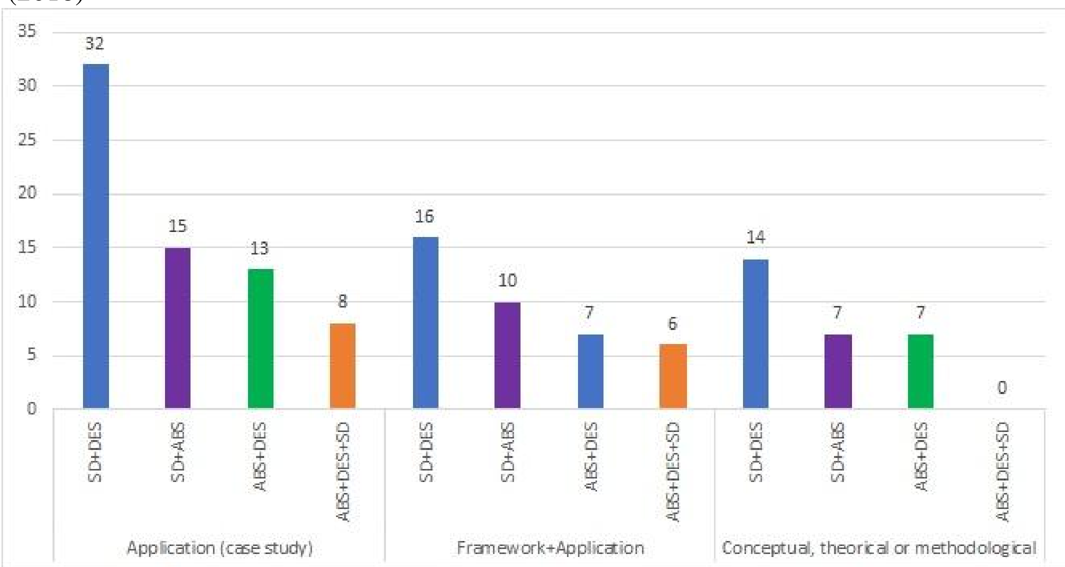
Studies on hybrid simulation have grown in recent years, but are still relatively small as shown in Figure 6. In 2016, only 21 papers were published, in all, only 57 papers were published in academic journals. Studies are being developed to investigate and solve specific problems, in addition to theoretical and conceptual studies (DJANATLIEV; GERMAN, 2015; BRAILSFORD et al., 2018).

Figure 6: Hybrid simulation literature, adapted from Brailsford et al. (2018)



Brailsford et al. (2018), also classified, according to Figure 7, the works in a combination of methods and applied studies, framework + application and theoretical, conceptual or methodological studies. Demonstrating the interest of researchers in using hybrid simulation in real-world problems and using SD and DES methods.

Figure 7: Combination of methods and types of studies in hybrid simulation, adapted from Brailsford et al. (2018)



Modelers need to model and simulate a real-world system that, for the most part, is complex. Using only one method can lead to complex modeling and still not represent reality and be accepting invalid assumptions or oversimplifying the model (DJANATLIEV; GERMAN, 2015; BRAILSFORD et al., 2018). Djanatliev e German (2015), describe that two terms have emerged to explain the combination of modeling techniques: "hybrid simulation" and "multiparadigmatic modeling" although, they suggest that the term hybrid simulation is better represented. Brailsford et al. (2018), refer to SD, DES and ABS as methods that have several techniques and discard the term paradigm, often used incorrectly. A model is the solution approach.

Brailsford et al. (2018) based on the paper by Morgan, Howick e Belton (2017), describe the modes of interaction among the simulation methods:

- Enrichment: simulation using a dominant method with less use of another method;
- Sequential: models with different methods executed sequentially so that the output of one is the input of the other;
- Interaction: models with different methods executed dynamically in time and space and interact cyclically among them;
- Integration: the perfect model, integrating two or more simulation methods in the same model.

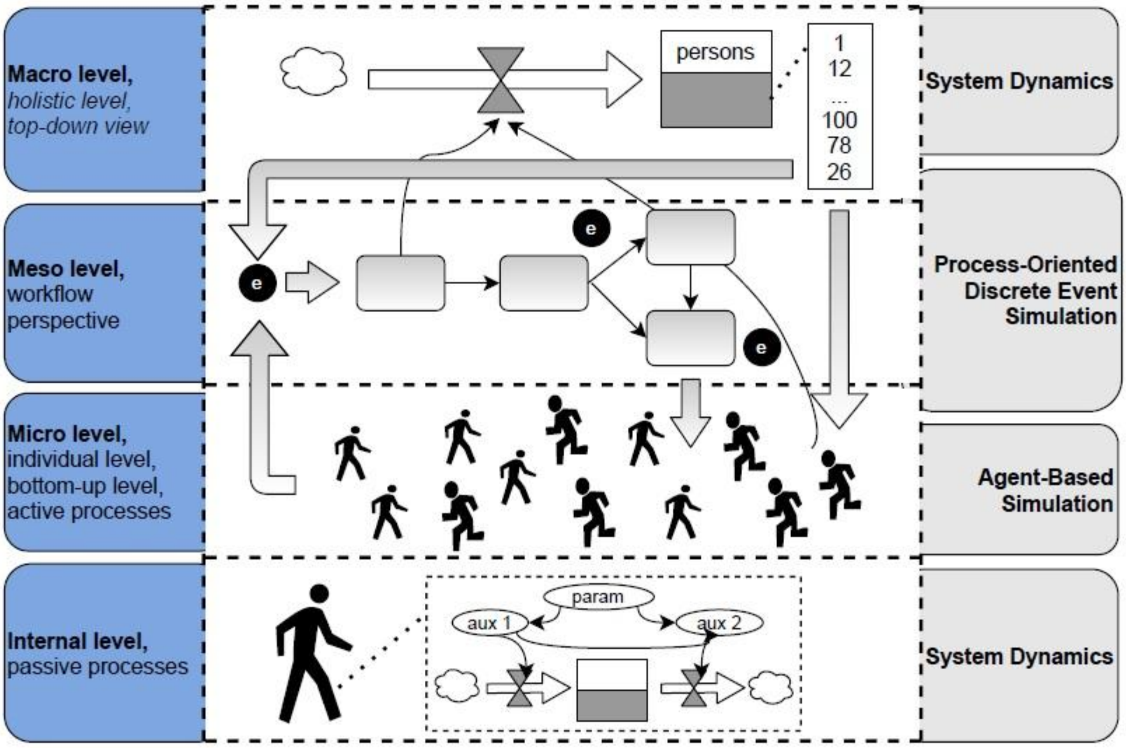
To be considered a hybrid model, some type of integration between the models is necessary. Integration can be automated, using commercial software, manually, copying and pasting data from one software to another and intermediate tools like Excel. The integration of ABS methods with DES offers a bottom-up approach to modeling systems (entity reactions), while SD and DES offers a top-down approach to modeling systems (manager reactions) (BRAILSFORD et al., 2018).

The tool that best developed the hybrid simulation aggregating the three main methods in a single software was Anylogic. The software has a graphical interface that facilitates the user, but when modeling complex systems some knowledge in Java is needed (DJANATLIEV; GERMAN, 2015; BRAILSFORD et al., 2018).

The challenge of hybrid modeling is to understand how each method can be used effectively with other simulation techniques so that each technique solves part of the problem (DJANATLIEV; GERMAN, 2015; MACAL, 2016). Conceptual modeling techniques and hybrid model validation are areas that need to be better explored (BRAILSFORD et al., 2018).

Before starting a hybrid simulation, it is necessary to identify the area, the problem and the scope of the simulation, as they may have different levels of abstraction. This step is important to determine which simulation approach will be applied. As shown in Figure 8, the System Dynamics (SD) method is more common in continuous structures with a macro level of abstraction, DES is used for flow and process simulation at the meso level, while ABS models the individual behavior at the micro level. Again the SD models at the internal level (DJANATLIEV; GERMAN, 2015).

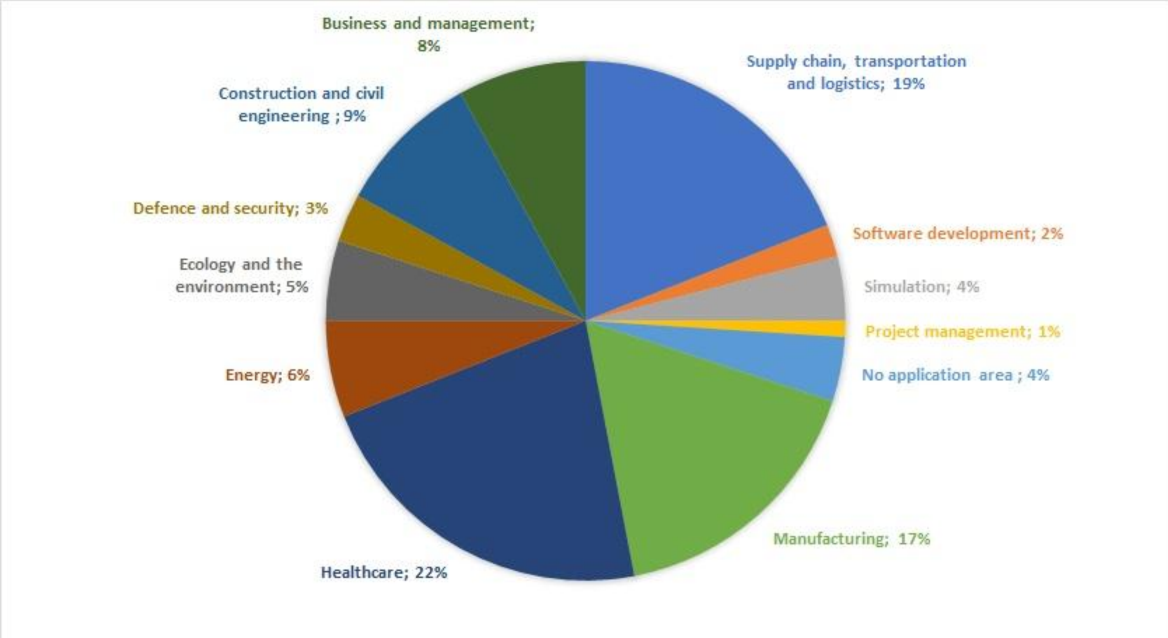
Figure 8: Simulation abstraction levels (DJANATLIEV; GERMAN, 2015)



By analyzing the level of abstraction of the problem to be simulated, as shown in Figure 8, it facilitates the decision to choose which simulation approach is the most suitable for the problem and whether only one simulation method is enough to solve the problem or whether a hybrid simulation is needed (DJANATLIEV; GERMAN, 2015).

The main area of application of hybrid simulation was health, as shown in Figure 9. According to Brailsford et al. (2018), the complexity of health services and the availability of existing models that provide a platform for hybrid simulation are factors that contribute to the number of publications.

Figure 9: Hybrid simulation study areas, adapted from Brailsford et al. (2018)



Health problems have many variables and it is very difficult to capture all of them in just one method (BRAILSFORD et al., 2018). Decision-makers have many complex situations at different levels of abstraction (DJANATLIEV; GERMAN, 2015).

At the macro level, the incidence and prevalence of diseases, epidemiological profile over time, demographic and economic variables are best represented by SD. The meso level is represented by workflows, such as hospital processes, emergency departments and triage, these flows are usually simulated by DES. At the micro-level, the active behavior of patients, generating unpredictable demand, is modeled by ABS. There is still the internal level, represented by special cases at the micro passive level, modeled by SD (DJANATLIEV; GERMAN, 2015; BRAILSFORD et al., 2018).

The complex structure of health services encompasses the concepts of queues, flows, behaviors and decision making. Individual methods are unable to capture all of these elements. Abdelghany, Eltawil e Abdou (2016), describe that the DES and ABS methods can include the details necessary to create a more realistic health simulation model.

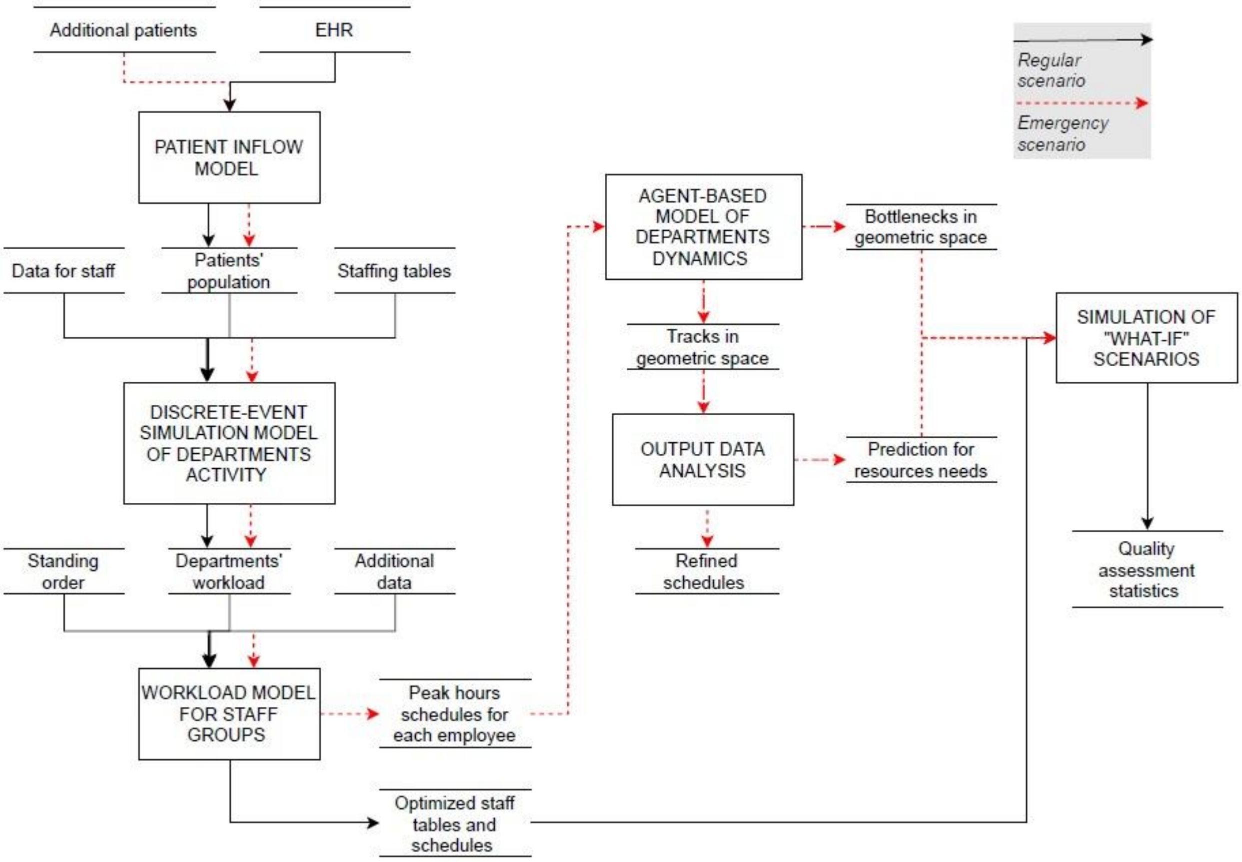
Simulation models that use purely ABS take a long time to build, due to the great need for data. A hybrid model using the DES and ABS methods is best represented, as DES can represent the general system and ABS only human behaviors, thus unifying the positive points of each (ABDELGHANY; ELTAWIL; ABDOU, 2016).

Kisliakovskii et al. (2017), present a simulation structure to assess health quality, from the perspective of managers. The study combines DES and ABS in a data flow process and was applied using data from the hospital information system at the Almazov National Medical Research Center.

According to Kisliakovskii et al. (2017), health is undergoing a transition from volume-based care to value-based care for the patient, through individualized and patient-centered care with more quality and effectiveness. However, these changes bring even more complexity to the process, generating more unstructured data.

In Figure 10, Kisliakovskii et al. (2017) present a structure that assesses the workload based on the hospital's real-time data flow. Data entry starts with the electronic medical record system, combined with access data and team schedule tables. Afterward, the DES is built, evaluating each step of the flow and resulting in the workload.

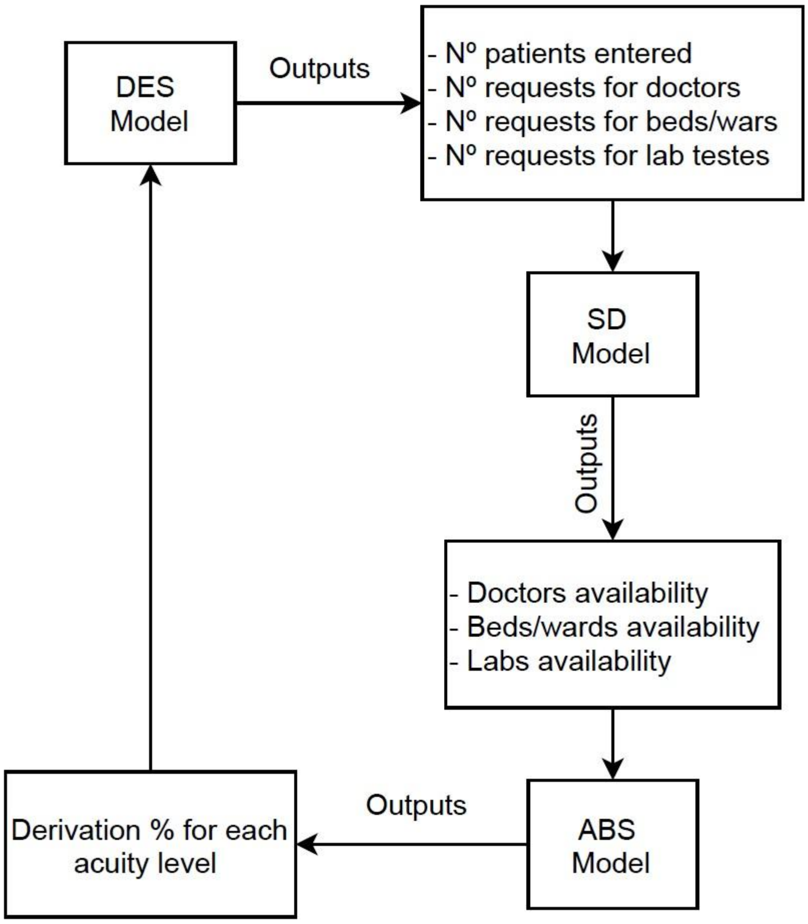
Figure 10: Data flow simulation framework (KISLIAKOVSKII et al., 2017)



In parallel, an ABS is built to assess emergency care not provided for in the DES model and to assess peak workload times. The dynamically generated data from the interactions between the agents, help in the decision making of resource allocation (KISLIAKOVSKII et al., 2017).

Abdelghany e Eltawil (2014), developed a framework integrating the three simulation methods and stated that there are advantages to simulating complex environments with integrated rather than individual approaches. In your model, an emergency department is modeled after the structure shown in Figure 11. Abdelghany e Eltawil (2014) use ABS to evaluate the best policy for patient diversion, DES to model operational details and SD to model the interrelationships between DE and other hospital units.

Figure 11: Model integrating the three methods (KISLIAKOVSKII et al., 2017)



In the model shown in Figure 11, the DES provides detailed information on the number of patients, medical requests, diagnostic requests and bed requests for the SD model. The SD model uses this data as input for a strategic analysis on the availability of doctors, laboratories and beds to select the best patient referral policy based on the level of accuracy modeled by ABS (ABDELGHANY; ELTAWIL, 2014).

In the search for papers that use the hybrid simulation combining DES and ABS, 4 papers were identified eligible for the criteria referred to in the subsection 2.2. Also, to add more data, 3 unidentified papers were added in the initial search. In Table 5 it is possible to identify which are the main agents modeled and which method is used for each stage of the simulation.

Table 5: Environments, agents and hybrid methods

Modeled environment	Authors	Agents	Steps modeled in DES	Steps modeled in ABS
Ambulance service Emergency department	Anagnostou A., Nouman A., Taylor S.J.E.	Emergency calls Patients Ambulances	Emergency department	Ambulance service
Ambulance service Emergency department	Nouman A., Anagnostou A., Taylor S.J.E.	Ambulances	Emergency department	Ambulance service
Ambulance service Emergency department	Hagtvedt R., Ferguson M., Griffin P., Jones G.T., Keskinocak P.	Ambulances Emergency department	Emergency department	Ambulance service
Ambulance service	Fakhimi et tal	Ambulances	Data generated by the ambulance flow	Ambulance service
Ambulance service	Roberto Aringhieri	Ambulances Operation center	Ambulance service flow	Interaction among ambulances Operation center
Emergency department	Mackay M., Qin S., Clissold A., Hakendorf P., Ben-Tovim D., McDonnell G.	Bed manager	Flow of patients	Bed manager
Radiology Center	Abdelghany, Mohammed Eltawil, Amr B	Doctors Receptionist Nurse RX RX Technician Nurse Nursing technicians	Flow of patients	Technical resources

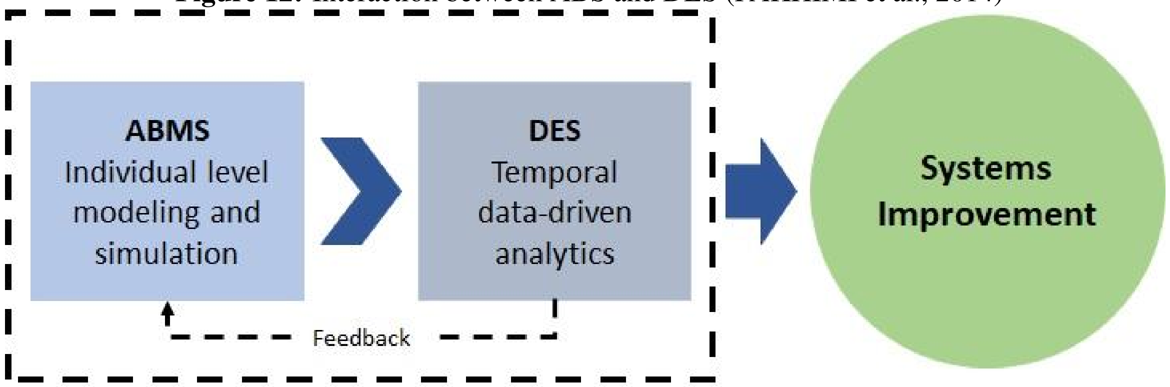
Anagnostou, Nouman and Taylor described two papers dedicated to a distributed simulation technique integrating existing DES and ABS models. The model integrated a central ambulance service to several emergency departments in the London region. The study aimed to demonstrate the use of hybrid DES and ABS simulation and to assess the behavior of the ambulance service in the face of increased emergency calls (NOUMAN; ANAGNOSTOU; TAYLOR, 2013a; ANAGNOSTOU; NOUMAN; TAYLOR, 2013)

With a similar objective, Hagtvedt et al. (2009) developed research addressing DES for emergency department flow, ABS for ambulance behavior, and game theory to apply patient referral strategies. They concluded that the health system will have better results by having a centralized agent to refer patients to emergency departments.

Also focused on ambulance services Aringhieri (2010), conducts a study at the Milan service. It uses DES to simulate the service flow and ABS to obtain interactions among ambulances and the operations center. They observed a performance improvement when the operations center assigns a new mission to an ambulance even without having arrived at its base.

In an unconventional model, Fakhimi et al. (2014) use ABS to individually model the behavior of ambulances in a London service and obtain results of response time, fuel consumption and CO2 consumption variables, after using this data to generate a flow DES and increase the sample. The objective is to simulate complex environments and analyze the best strategies to improve the results of the service from the point of view of the Figure 12.

Figure 12: Interaction between ABS and DES (FAKHIMI et al., 2014)



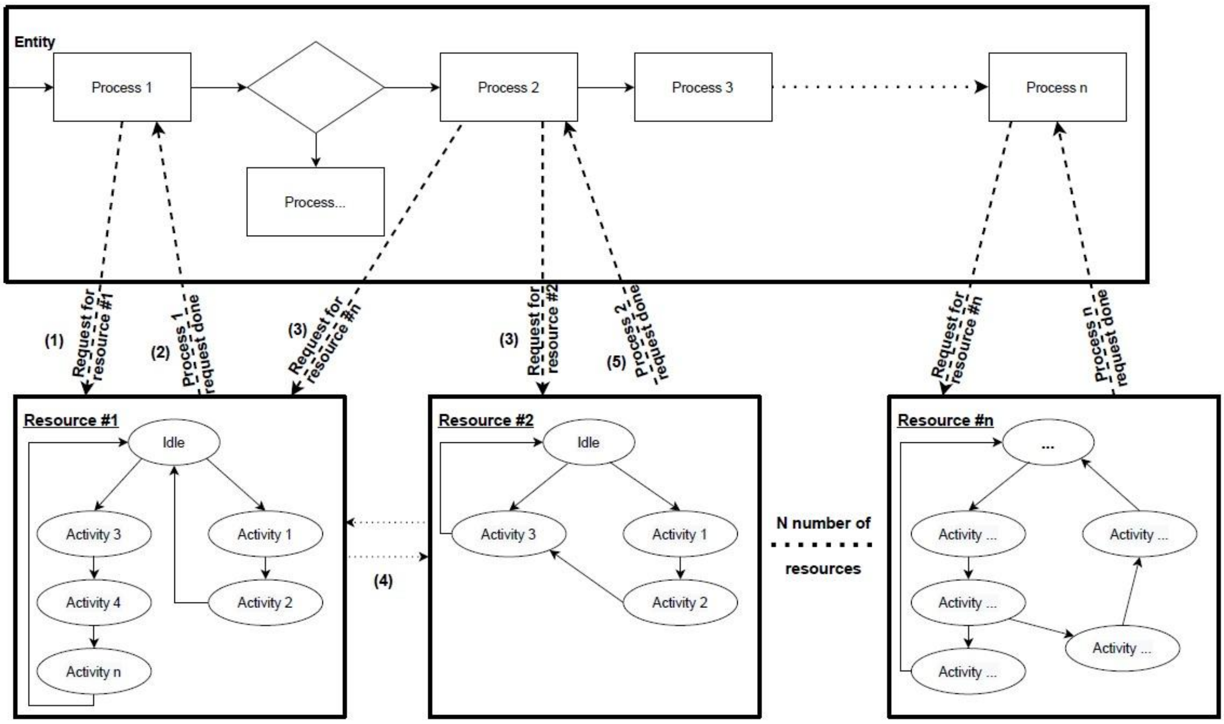
In the study, the data generated in the ABS scenarios are the inputs of the DES model that receives temporal data and indicators from the simulated scenarios. With DES analyzes the data received and finds the best set of input parameters. After the feedback loop occurs, DES suggests a new set of input parameters for the ABS model to achieve the defined goals

(FAKHIMI et al., 2014).

In addition to ambulance services, Mackay et al. (2013) conducted a study in an emergency department at a hospital in South Australia to demonstrate that the simulation can be used to improve understanding and assist in decision making regarding the flow of patients and issues bed management. The system dynamics method was used to create the health condition policy, a DES to build a patient flow, and an ABS to develop a bed manager. The authors emphasized multidisciplinary collaboration for the success of the model.

To demonstrate the complexity of modeling health systems, Abdelghany, Eltawil e Abdou (2016) developed a DES model for patient flow and an ABS model for the behavior of resources in a radiology center in Egypt. From the comparison of the length of stay of patients in the model with the real system, they concluded that it is possible to use a decision-making tool that analyzes tasks and resources. The model by Abdelghany, Eltawil e Abdou (2016) is represented in Figure 13. In the upper part it represents DES through the patient flows, in the lower part, there is the ABS and the activities of the different agents. The dashed lines are the interactions between the two methods.

Figure 13: DES and ABS integration model (ABDELGHANY; ELTAWIL; ABDOU, 2016)



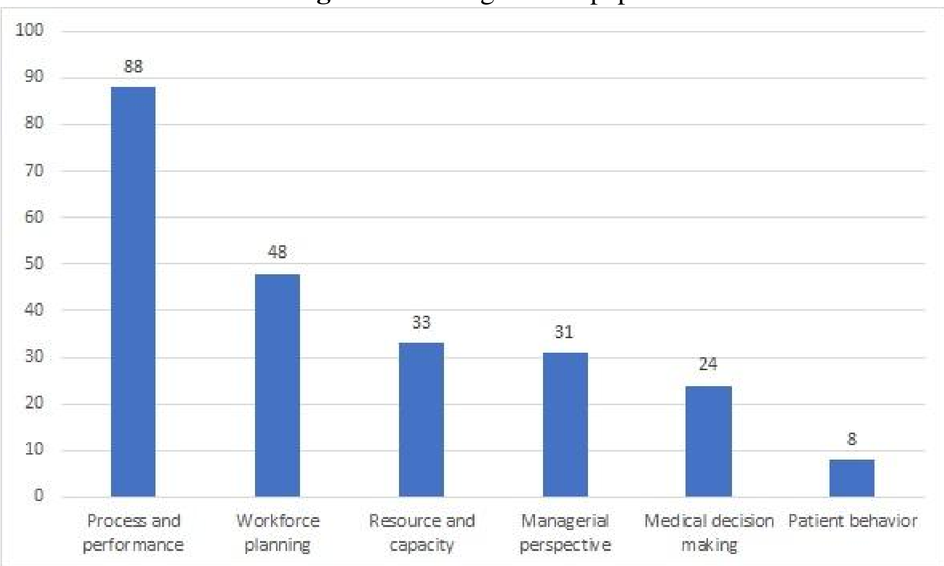
The model proposed in Figure 13 by Abdelghany, Eltawil e Abdou (2016) was applied in a radiology center. At work, the verification and validation steps together with administrators and patient arrival patterns are highlighted. The "Length of Stay" indicator of the computational model was also compared with the real-time of the unit. The study concludes that the two methods are complementary and that further studies to improve the agents' activities and their decision making would improve the model.

Several models and methods have been developed for the health system to improve and manage problems such as patient flow, waiting time, resource allocation, and patient referral policies. Simulation models assist managers in making decisions (ABDELGHANY; ELTAWIL, 2014). Therefore, it is important to have metrics established to evaluate the effectiveness of the simulation models.

3.6 Evaluation categories and criteria

The categories, described in Subsection 2.2, demonstrate six ways of classifying papers, which can be classified into more than one category. The 103 papers evaluated were classified, and the results are shown in Figure 14.

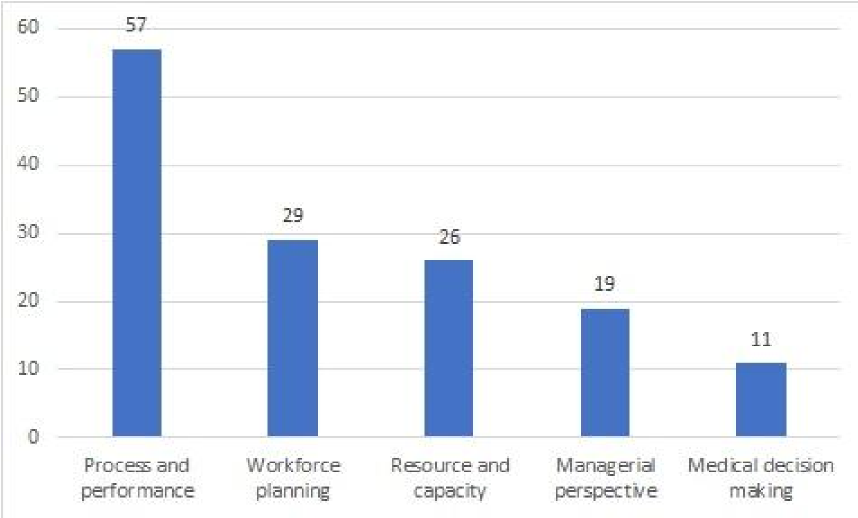
Figure 14: Categories of papers



It is possible to observe that the categories Process and Performance, Workforce Planning and Resource and Capacity are more prevalent in simulation studies. The DES and ABS methods have a more tactical and operational character, mainly because they solve problems related to the length of stay, waiting and the allocation of resources as observed by Salmon et al. (2018).

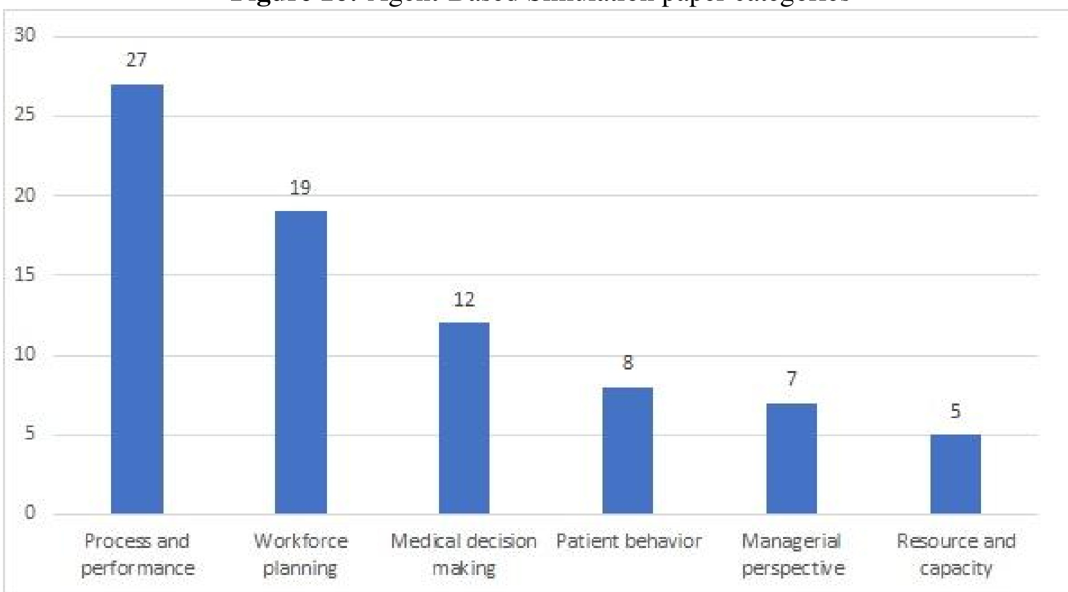
As more papers are referring to DES, it is necessary to stratify the data above for each method studied, enabling a more reliable analysis. Figure 15 shows the results for the DES method:

Figure 15: Discrete event simulation papers categories



The results for the DES papers demonstrate that this method is more applied for evaluating and improving processes and performance of emergency departments, confirming Zhang (2018). In this method, there is no study on the patient's behavior, in which it becomes complex. The results of the ABS method are shown below in Figure 16.

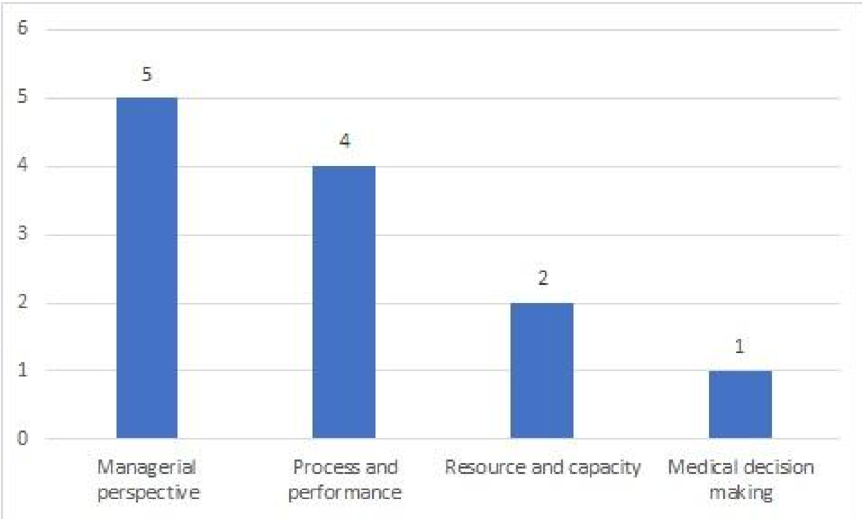
Figure 16: Agent-Based Simulation paper categories



As demonstrated in the literature, by Siebers et al. (2010) and Macal (2016), with the ABS method it is possible to simulate the patient's behavior, in the results, 8 papers were identified in this category. However, like the DES, the two prevalent categories study the processes and the planning and allocation of human resources in the ED.

Different results are presented in the hybrid method, in Figure 17, the results of the method integrating DES and ABS are demonstrated.

Figure 17: Hybrid Simulation paper categories



The main result is the category of Managerial Perspective. The hybrid method uses the potentials of the DES and ABS methods so that what is possible to solve with just one method is not highlighted in the hybrid as Brailsford et al. (2018). The hybrid method uses the ability to model DES flows with the ability to model ABS behavior, allowing the modeling of more complex systems according to Abdelghany, Eltawil e Abdou (2016), thus the managerial perspective assesses the behavior of ambulances or the central beds in the demand of the emergency departments, enabling more strategic decision-making.

3.6.1 Simulation inputs

The inputs and outputs of the papers were analyzed to contribute to the analysis of the data needed to build and choose which simulation method to use. The main inputs used are shown in Table 6.

The main inputs used, in the general column, in Table 6 are the arrival of patients and the priority of patients, which includes the number, schedule, frequency and risk degree (acuity) of patients entering the emergency department, these data are important for simulate service flow and demand. In the sequence, data of quantity, shifts, types of technical resources such as

Table 6: Inputs identified in the papers of each method

Inputs	General	DES	ABS	Hybrid
Arrival of patients	102	63	33	6
Service priority	83	58	23	2
Time of each step of the process	77	55	20	2
Quantity of technical resources	76	53	19	4
Quantity of equipment / rooms and physical resources	37	32	2	3
Cost of technical resources	14	6	8	
Patient discharge	9	5	3	1
Patient waiting time	9	6	1	2
Team experience (junior and senior)	8		8	
Patient lenght of stay	5	4		1
Medical specialties	3		3	
Quantity and types of surgery	3	3		
Transfer rate	3	1	1	1
Use of equipment	3	1		2
Journey distance	2			2
Location of patients	2		1	1
Location of emergency departments	2		2	
Number of patients waiting to be seen	2	1		1
Ambulance speed	2			2
Service capacity	1			1
Emergency calls	1			1
CO2	1			1
Fuel consumption	1			1
Distance from emergency department patients	1		1	
Opening hours	1		1	
ED layout	1	1		
Patient transfer location	1	1		
Movement of technical resources	1	1		
Number of patients who in the AMI protocol	1	1		
Number of patients using a ventilator	1	1		
Population of the region	1		1	
Probability of error in the triage room	1		1	
Probability of doctor asking for tests	1		1	
Number of Emergency Departments	1			1
Financial income	1			1
Time to medical care	1	1		
Ambulance response time	1			1

doctors, nurses, triage nurses and receptionists are also used and after the equipment, rooms and physical areas necessary to evaluate the capacity and use of the service.

The inputs were stratified by the method to provide a more detailed analysis. In the DES column shows the main inputs for developing the operational flow of the simulation, highlighting the time of each process and the number of technical resources. Important data to develop the process. Afterward, in the ABS column are presented in addition to the already prevalent inputs, data that can influence behavior such as team experience, probability of errors in the triage room, probability of the doctor requesting for tests stands out. Finally, the inputs of the Hybrid method are shown, integrating DES and ABS in the last column. The input data is already more distributed, mainly because more studies are evaluating the behavior of ambulances. The outputs for each simulation method are shown below.

3.6.2 Simulation outputs

In the same way as the Inputs, it was identified in Table 7 the Outputs generated from the simulations described in the papers evaluated. The length of stay and the waiting time for patients are the most prevalent results in Table 7 and are the biggest problems that impact patient satisfaction as exposed by Silva et al. (2016); Yousefi e Ferreira (2017) and Rech et al. (2018). As well as the use of technical resources, equipment, rooms and physical resources that are the other factor to solve according to Yarmohammadian et al. (2017) and Rech et al. (2018).

The outputs were also stratified by the simulation method, as shown in the DES column. The outputs of the DES column represent the main results of the general data. In the ABS column, there are slightly different results. ABS outputs are a little more specific and may be due to behaviors such as patients who leave without being seen and the team's experience.

The hybrid methods column is presented for the outputs of the hybrid simulation. Due to the lower number of papers, there are also fewer outputs, although, it is noticed that the patient's length of stay is the first output in all methods. For hybrid simulation, the outputs are more varied, containing more managerial data such as financial income and fuel and CO2 consumption.Also, the flow of data, such as waiting time, response time.

3.6.3 Simulation metrics from emergency departments

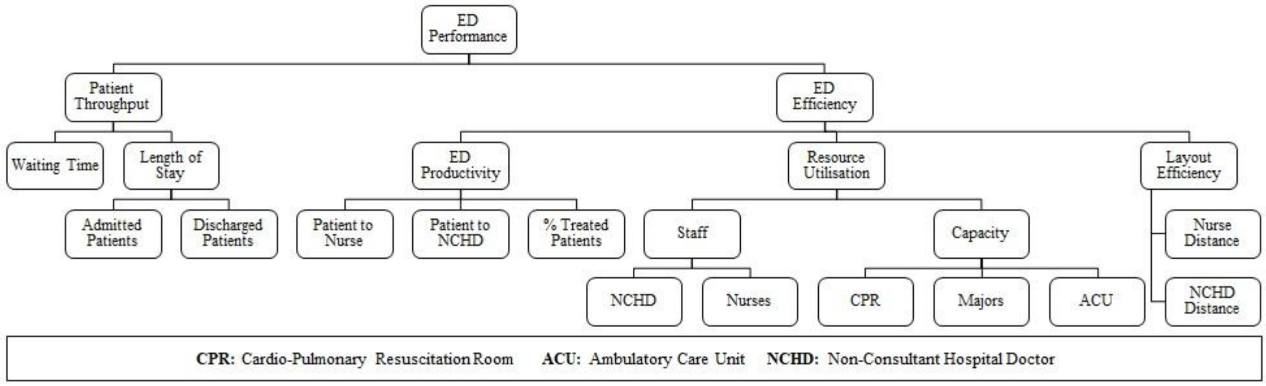
Indicators are performance metrics used by emergency departments to assess operation and quality of service (GUL; GUNERI, 2015). Abo-Hamad e Arisha (2013), organize the

Table 7: Outputs identified in the papers of each method

Outputs	General	DES	ABS	Hybrid
Patient lenght of stay	73	53	18	2
Patient waiting time	61	46	14	1
Use of technical resources	38	31	6	1
Use of equipment / rooms and physical resources	25	24		1
Time to medical care	18	13	5	
Cost of technical resources	12	7	5	
Patients who leave without being seen	12	5	7	
Number of patients seen	9	7	2	
Patient discharge	5	3	2	
Team experience	5		5	
Number of patients waiting to be seen	5	1	4	
Transfer rate	5	4	1	
Time to triage service	4	2	1	
Time to hospitalization	3	3		
Patient movement	2	1		1
Quantity of technical resources	2	2		
Computational time	2	1		1
Ambulance response time	2			2
Patient care time	2	1	1	
Improperly discharged patients	1		1	
Service capacity	1	1		
Arrival of patients	1	1		
CO2	1			1
Fuel consumption	1			1
Equipment cost	1	1		
Discharge destination	1	1		
Patient queuing frequency	1	1		
Hospitalization refusal rate	1	1		
Information generated to readjust location resources	1		1	
Movement of technical resources	1	1		
Number of urgent visits	1			1
Number of clinical evaluations	1	1		
Number of interactions among technical resources	1			1
Number of delayed hospitalizations	1	1		
Number of deaths	1		1	
Number of patients admitted to hospital	1	1		
Number of ill-allocated patients	1	1		
Number of patients in the clinic	1	1		
Number of services per patient	1	1		
Patients' opinion	1		1	
Percentage and risk of patient identified with delay	1	1		
Number of clinics	1	1		
Number of exams	1	1		
Financial income	1			1
Surgery cancellation rate	1	1		
Travel time to the Emergency Department	1		1	
Ambulance diversion time	1			1
Triage time	1	1		
Doctor travel time	1	1		

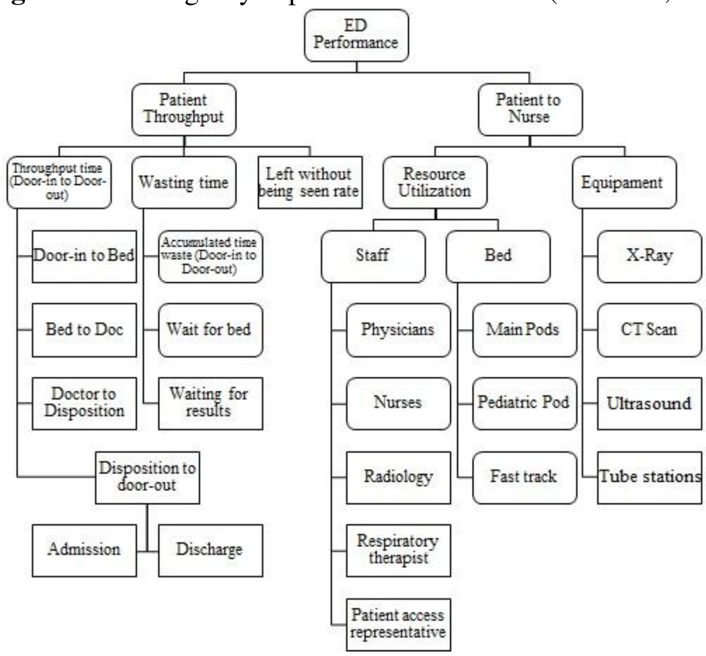
main emergency department indicators as shown in Figure 18.

Figure 18: Emergency department indicators (ABO-HAMAD; ARISHA, 2013)



Like Abo-Hamad e Arisha (2013), Oh et al. (2016) also developed a structure of indicators for the emergency department, represented by Figure 19.

Figure 19: Emergency department indicators II (OH et al., 2016)



Gul e Guneri (2015), conducted a literature review of studies in the emergency department and divided the emergency department indicators into five groups:

1. Average time: waiting to see the doctor, make a diagnosis, make a treatment, for the triage, records, discharge and total average time spent in the emergency department;

2. Productivity: number of patients who saw the doctor, in queues, waiting, released and left without being seen;

3. Utilization: doctors, nurses, technicians, administrative staff, equipment and beds;

4. Costs: staff labor and total emergency department costs;

5. Others: overcrowding, sigma level, saving rate.

Most of the studies identified by Gul e Guneri (2015) use waiting times and processing times as a metric for the simulation in emergency departments. They also comment that few measure the rate of patient downtime. They also comment that few measure the rate of patient downtime.

In addition to the indicators for measuring the simulation result in the emergency department, it is also relevant to evaluate metrics from the simulation methods themselves. Naseer, Eldabi e Young (2010), developed the RIGHT Toolkit, based on the literature review, a tool for comparison and selection of modeling and simulation methods was built. A list of 23 methods was identified, for each method, the researchers identified, based on literature reviews and expert opinion, the necessary resources being time, money, knowledge, data and the expectations of results such as level of insight and level of detail (NASEER; ELDABI; YOUNG, 2010).

The study by Naseer, Eldabi e Young (2010), seeks to understand the potential of applying simulation methods if the techniques were accessible in the health environment. Allowing managers to choose the best method based on the problem and a context of available resources to develop the simulation. The criteria for comparing the simulation methods are processing time, money/cost to develop the simulation, knowledge about the problem and need for data. The requirements for each of the criteria are shown in Table 8.

Table 8: Simulation resource requirements, adapted from (NASEER; ELDABI; YOUNG, 2010)

Scale\ Parameters	**1**	**2**	**3**	**4**	**5**
Time	hours (t<= a day)	days (a day<t<= a week)	weeks (a week <t<= a month)	months (a month <t<= a year)	years (t>a years)
Money	tens (m<= 100)	hundreds (100 <m<=1k)	thousands 1k<m<=10k)	10 thousands (10k <m<=100k)	100 thousands (m>100k)
Knowledge	none	Limited	Moderate	Expert	Complete
Data	none	Guesstimate	Some raw	Good statistics	All type

With this information, Jun et al. (2011) apply the model to compare and select the most appropriate methods for certain types of problems in the management of health services. Based on Naseer, Eldabi e Young (2010), Jun et al. (2011), details the criteria..

The time corresponds to the period required for the development and processing of the simulation. The money/cost refers to the amounts needed to purchase software, hardware, and acquire knowledge. Knowledge refers to qualitative knowledge about the simulation problem, which is necessary to develop the model. Finally, the data refer to the required quantitative data.

The last two requirements are qualitative, so Jun et al. (2011) detail the parameters presented in Figure 8 for understanding:

Knowledge: what knowledge do you have about the problem?

- New problem: without prior knowledge about the problem;
- Limited knowledge: knows some aspects of the problem;
- Moderate knowledge: has access to relevant knowledge about the problem, but without knowledge of its implications;
- Expert knowledge: has access to knowledge and comprehends its implications;
- Complete knowledge: knows the problem, its implications and has access to a team of specialists in the subject.

Quantitative data: data required for the model:

- None: without quantitative data;
- Guesstimate: data and empirical trends;
- Raw data: some statistical data;
- Statistical data: good data with financial and operational histories;
- Access all types of data: good statistical data and relevant knowledge about the problem.

The application of the tool for comparison and selection of modeling and simulation methods addressed by Jun et al. (2011), helps health managers to understand the appropriate methods but does not capture the complexity faced by managers when applying real problems. Thus, Jun et al. (2011), suggest the development of a better characterization of the categories of problems faced in health services. As well as helping to specify the necessary inputs and expected outputs for each method applied to each problem, bringing more detailed examples.

In the next chapter, the conceptual model, the computational models and the discussion of the results generated will be presented. Assessing the applicability of each method in an emergency department.

4 RESULTS

Chapter 4 presents the development, results and discussions on the stages of the work. In the first section, the conceptual model is presented covering the study environment, the ED flowchart, the collection of data and technical resources, the layout of the emergency department, and the validation of the conceptual model. After the computational models are demonstrated, the analysis of the input data and the development of the four simulation models. All models are validated.

Next, the results of each simulation method are assessed and evaluated for the categories, metrics, inputs, and output generated. In this way, it is possible to assess the results and develop an orientation framework of which simulation models are most appropriate for each need in an emergency department.

4.1 Conceptual model

The conceptual model is an abstraction from the real model that, according to Will M. Bertrand e Fransoo (2002) and Robinson (2008) facilitates the researcher to identify which objectives, inputs, outputs, assumptions and simplifications will be necessary for the development of the computational model.

In this section, the conceptual model is detailed, starting with the description of the study environment and the construction of the process flowchart and the layout of the emergency department. In this way, it is possible to collect data from the ED and technical resources. Finally, the conceptual model is validated.

4.1.1 Study environment

The hospital under study is a private Emergency Department and Day Hospital in the state of Rio Grande do Sul, Brazil. The service unit has emergency services, outpatient procedures, complementary diagnostic tests (radiology and ultrasound), low and medium complexity surgeries and ambulance service. The unit contains 27 observation beds for up to 12 hours and hospitalization beds for up to 24 hours. After this period, they are transferred to a hospital of greater complexity. This unit belongs to a private hospital complex with over 40 years of existence. The company has 1500 employees, more than 500 doctors, two day hospitals, two 24-hour emergency departments, a low and medium complexity hospital with about 60 beds, Adult ICU and Neonatal ICU, operating room, diagnostic services such as

X-ray, tomography and magnetic resonance.

The company has a well-structured quality and patient safety management with more than 70 mapped processes, indicators divided into structure, processes and results, and more than 2,000 standardized documents. The hospital complex is located in a region that mainly serves 11 municipalities in southern Brazil. It is linked to a private health system that has coverage across the country with more than 119 own hospitals, 2,245 partner hospitals, and 116,000 doctors.

In 2018, the unit under study received 182,269 patients in total, of which 78,125 were emergency visits, in 2019 there were 149,082 visits, 89,675 of which were emergency. Most of the clients come from health insurance companies, followed by other types of insurance and private clients, the unit does not receive patients from the Unified Health System (SUS). Patient satisfaction at this unit is 93.4% in 2018 and 86.8% in 2019 (there is a change in the research method between 2018 and 2019).

The emergency service of the studied unit aims to provide medical and nursing care in an agile manner, based on ethical, technical and scientific principles to clients seeking emergency care. The indicators that currently measure the process are:

- Time of medical care for the patient classified as very urgent, urgent, little urgent or not urgent;
- Triage time;
- Response time of the Pulmonary Cardiac Resuscitation team after activation;
- Number of Cardiopulmonary Arrests Reverted by PCR Teams.

The services analyzed in this study are limited to the emergency environment. It includes clinical, cardiological, traumatological and pediatric visits until hospitalization in the Observation beds. For this study, the Observation area is defined as the place where patients are under medical and assistance monitoring for up to 12 hours, patients await the return of exams and receive intravenous medications. Admission to the day hospital is conceptualized as patients who are monitored by routine physicians and nursing, nutritional and pharmaceutical care for up to 24 hours, after which patients are referred to another hospital in the more complex network. This service is not modeled in the study.

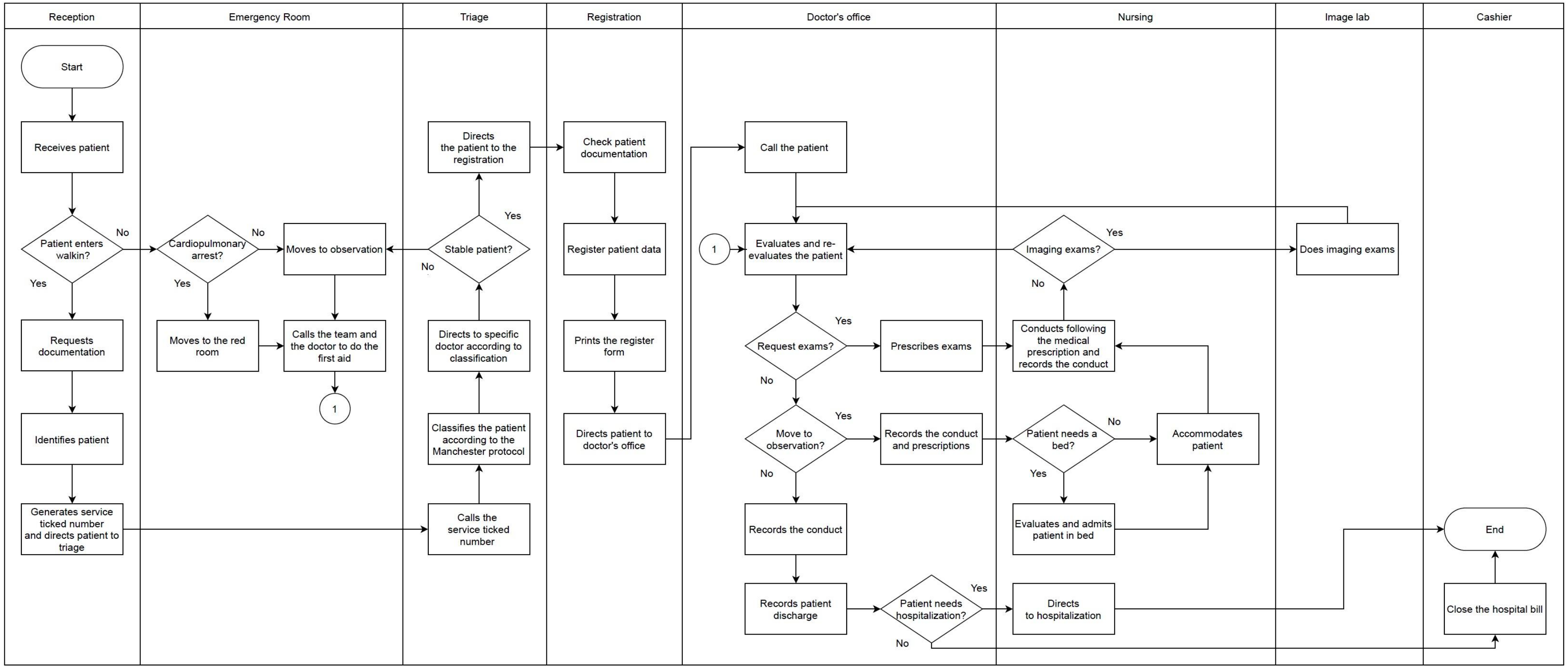
In 2014, the hospital started to implement the health information system (HIS) and in 2017 it started to implement the digital certificate replacing the signature of the technical professionals on paper. With this improvement, it was possible to improve and automate care processes and make them digital, improving the experience and safety of patients and professionals, in addition to qualifying care records.

4.1.2 Process flowchart

From the analysis of the organization's qualitative documents and face-to-face observation, a flowchart was drawn, as shown in Figure 20, of the emergency department process to understand the variables necessary to develop the computational model. The emergency process begins with the generation of a ticket number with the guidance of a reception assistant after the patient goes to the triage where a nurse evaluates the patient according to the Manchester protocol to identify the degree of risk (acuity) of the patient and his priority of medical care to organize the queue.

After the patient goes to the reception, checks the health plan coverage, makes his registration and is directed to the doctor. The visit with the doctor defines the treatment conduct that can be medical discharge, referral to the observation area for medical follow-up, referral for further investigative tests, or referral for hospitalization. The patient who is referred for observation can be accommodated in an adult or pediatric chair in mild cases or a bed in more severe cases. The nursing team monitors and executes the procedures in the observation according to medical conduct. The exams can be clinical laboratories that are collected by the nursing team itself and sent to an external laboratory or conducted by radiologists when X-ray or ultrasound. All exams are presented for medical evaluation. The patient can be admitted or discharged. Upon discharge, he goes through the cashier to close the hospital bill.

Figure 20: Process flowchart



The process flowchart is important for identifying subprocesses and connections between patients and resources. These variables are later used in the computational model (OH et al., 2016).

4.1.3 Emergency department layout

The unit is composed of the service by the emergency department and day hospital, although, this study is only prepared considering the emergency care in which emergency patients are treated. In Figure 21, the locations of each step of the flow are shown.

Figure 21: Emergency department layout

As shown in Figure 21, the unit has a service desk to generate ticket number, triage room, reception for registration, three clinical offices (OC), two pediatric offices (PO), one cardiology office (CDO), and one traumatological office (TO). In observation, there are 6 adult chairs, 7 pediatric chairs, 14 observation beds.

In addition to the simulated locations, the emergency department also has three outpatient elective rooms, three operating rooms, an electrocardiogram room, two X-ray rooms and two ultrasound rooms.

4.1.4 Data collect

Data were collected from the institution's electronic medical record software and hospital information database. The data obtained were: date and time of service ticket number generation; date and time of screening (triage); date and time of registration; date and time of medical care; date and time of the referral for observation; date and time of discharge. Also, data on the type of care and degree of risk (acuity) were collected to define the prioritization of visits.

Records are entered into the system by different professionals:

- Reception Assistant: generates the ticket number and the system records the date and time of the activity;
- Triage Nurse: registration of the triage and the system records the date and time automatically;
- Receptionist: registers patient information, and the system records the date and time automatically;
- Nurses and Observation Nurses: records changes and the system records the date and time automatically;
- Doctors: records the medical visit and the system records the date and time automatically;
- Cashier Assistant: records hospital discharge and the system records the date and time automatically.

In total, 78,124 records were collected in the emergency department corresponding to the period from 01/01/2018 to 12/31/2018. All records collected do not contain any information that can identify the patient or the professionals. The records are structured according to Figure 22.

If any professional does not register in the system, that step is not recorded.Every patient who accesses the emergency department needs an attendance record, so there are not many inconsistencies in the early stages. However, it can happen that the professional registers after the patient leaves, distorting the records. The data found with blank or off-curve records were medical records. In this case, these records were not considered when creating the probability distribution.

Figure 22: Service data

Risk	Medical Specialty	Date and Hour Service Ticket Number	Date and Hour Call Triage	Date and Hour Start Triage	Date and Hour End Triage
NOT URGENT	GENERAL CLINIC	1/16/18 1:13 PM	1/16/18 1:13 PM	1/16/18 1:14 PM	1/16/18 1:16 PM

Date and Hour Call Registratio	Date and Hour Start Registratio	Date and Hour End Registratio	Date and Hour Call Medical Car	Date and Hour Start Medical Car	Date and Hour End Medical Car
1/16/18 1:27 PM	1/16/18 1:18 PM	1/16/18 1:21 PM	1/16/18 1:23 PM	1/16/18 1:36 PM	1/16/18 1:41 PM

Date and Hour Discharge	Lenght of stay
1/16/18 3:33 PM	2:20:14

Date and Hour Prescription	Local	Date and Hour Discharge	Observation time
27/3/18 10:14 PM	CHAIR 03	27/3/18 11:12 PM	00:58:00

Table 9: Probabilities of patient arrivals by acuity and by specialty.

TRIAGE/ SPECIALTY	CARDIOLOGY	GENERAL CLINICAL	PEDIATRICS	TRAUMA TOLOGY	TOTAL
EMERGENCY	0,00%	0,03%	0,02%	0,00%	0,05%
VERY URGENT	0,52%	1,04%	2,85%	0,06%	4,46%
URGENT	0,90%	10,19%	2,59%	1,01%	14,69%
LITTLE URGENT	1,11%	48,20%	22,82%	7,10%	79,23%
NOT URGENT	0,02%	1,01%	0,07%	0,47%	1,57%
TOTAL	2,54%	60,47%	28,35%	8,64%	**100,00%**

On the same basis as the attendance data, it is possible to collect the acuity data, determining the priority. Table 9 shows the probabilities of patient arrivals by acuity and by specialty.

From the registration data, it is possible to calculate the average service times and waiting times, unifying with the triage information in Table 9, Table 10 is generated, including the time of arrival of patients and the times of each stage of the process and total emergency department time. Considering W = Wait and T = Time.

Table 10: Average time for service

Triage/Specialty	Arrival	W_Triage	T_Triage	W_Regis	T_Regist	W_Medical	T_Medical	T_Exam	T_LOS
EMERGENCY	**0:05:57**	**0:02:42**	**0:02:01**	**0:00:45**	**0:03:12**	**0:16:19**	**0:09:02**	**1:37:05**	**2:25:35**
CARDIOLOGY	0:13:16	0:04:59	0:02:39	0:00:00	0:03:41	0:05:40	0:12:04	0:04:43	0:30:49
GENERAL CLINICAL	0:05:56	0:02:36	0:02:02	0:00:31	0:03:03	0:11:11	0:09:40	1:42:08	2:30:02
PEDIATRICS	0:05:23	0:02:42	0:01:57	0:01:15	0:03:25	0:27:01	0:07:39	1:34:52	2:26:11
VERY URGENT	**0:06:40**	**0:04:29**	**0:02:35**	**0:01:26**	**0:02:55**	**0:17:23**	**0:12:03**	**2:58:04**	**3:47:12**
CARDIOLOGY	0:06:13	0:04:47	0:02:49	0:01:29	0:02:59	0:12:57	0:11:20	2:53:43	3:32:49
GENERAL CLINICAL	0:06:59	0:04:34	0:02:33	0:01:19	0:03:03	0:15:25	0:12:22	3:00:59	3:55:46
PEDIATRICS	0:06:39	0:04:24	0:02:34	0:01:28	0:02:49	0:19:10	0:12:03	2:58:10	3:47:16
TRAUMATOLOGY	0:06:00	0:04:40	0:02:28	0:01:39	0:04:07	0:13:17	0:12:56	2:39:57	3:23:44
NOT URGENT	**0:07:06**	**0:04:30**	**0:02:34**	**0:01:24**	**0:02:51**	**0:15:47**	**0:12:15**	**2:57:27**	**3:45:15**
CARDIOLOGY	0:06:15	0:01:14	0:02:41	0:01:30	0:02:40	0:18:24	0:09:47	1:40:53	2:12:56
GENERAL CLINICAL	0:06:08	0:04:35	0:02:32	0:01:25	0:02:52	0:15:00	0:12:26	2:58:33	3:48:28
PEDIATRICS	0:06:23	0:04:19	0:02:40	0:01:39	0:02:41	0:21:12	0:10:10	3:27:09	4:13:47
TRAUMATOLOGY	0:09:19	0:04:27	0:02:36	0:01:20	0:02:50	0:16:48	0:12:16	2:53:16	3:37:11
LITTLE URGENT	**0:07:00**	**0:04:35**	**0:02:33**	**0:01:28**	**0:02:50**	**0:16:22**	**0:12:02**	**2:56:34**	**3:46:23**
CARDIOLOGY	0:06:51	0:04:36	0:02:20	0:01:24	0:02:57	0:15:24	0:11:47	2:38:34	3:16:06
GENERAL CLINICAL	0:06:59	0:04:37	0:02:33	0:01:27	0:02:51	0:15:07	0:12:02	2:57:46	3:47:55
PEDIATRICS	0:07:03	0:04:33	0:02:34	0:01:29	0:02:48	0:18:59	0:12:09	2:54:30	3:45:12
TRAUMATOLOGY	0:06:59	0:04:34	0:02:35	0:01:27	0:02:48	0:17:40	0:11:45	2:57:54	3:44:32
URGENT	**0:07:16**	**0:04:44**	**0:02:36**	**0:01:26**	**0:02:49**	**0:16:12**	**0:12:16**	**2:56:52**	**3:46:13**
CARDIOLOGY	0:08:44	0:05:16	0:02:45	0:01:26	0:02:47	0:14:59	0:12:09	2:56:59	3:34:04
GENERAL CLINICAL	0:07:12	0:04:40	0:02:34	0:01:25	0:02:48	0:15:19	0:12:21	2:56:24	3:46:51
PEDIATRICS	0:07:09	0:04:39	0:02:41	0:01:28	0:02:54	0:19:39	0:12:03	2:53:42	3:45:05
TRAUMATOLOGY	0:06:55	0:05:09	0:02:40	0:01:26	0:02:50	0:18:28	0:11:59	3:09:38	3:53:48
Average time	**0:07:01**	**0:04:36**	**0:02:34**	**0:01:27**	**0:02:50**	**0:16:23**	**0:12:04**	**2:56:39**	**3:46:20**

The average time of patients admitted to the observation beds, adult chairs and pediatric chairs were also collected and are represented by the Table 11.

Table 11: Observation Average Time

Observation	Time
PEDIATRIC CHAIR	04:06:09
ADULT CHAIR	04:33:31
BED	07:58:18

In Subsection 4.2.1, the service data collected are analyzed by identifying the probabilistic distributions used in the computational model. The next subsection details the technical resources of the emergency department.

4.1.5 Technical resource data collection

Technical resource data were collected from the people management system and are shown in Table 12, organized by shift. Technical resources are considered professionals who work with patient care. These resources are essential in the computational model for analyzing the capacity and use of resources in the emergency department, as identified in the literature.

Table 12: Technical resource data

Technical resources	Start shift	End shift	Quantity	Process
	7:00 AM	1:00 PM	1	
Reception Assistant	1:00 PM	7:00 PM	2	Generates service ticked number and directs patient to triage
	7:00 PM	7:00 AM	2	
	7:00 AM	1:00 PM	3	
Receptionist	1:00 PM	7:00 PM	3	Register patient data
	7:00 PM	7:00 AM	1	
	7:00 AM	1:00 PM	2	
Triage Nurse	1:00 PM	7:00 PM	1	Classifies the patient according to the Manchester protocol
	7:00 PM	7:00 AM	1	
	7:00 AM	1:00 PM	1	
Observation Nurse	1:00 PM	7:00 PM	1	Evaluates and admits patient in bed
	7:00 PM	7:00 AM	1	
	7:00 AM	1:00 PM	6	
Technician Nursing Obs	1:00 PM	7:00 PM	6	Conducts according to medical prescription
	7:00 PM	7:00 AM	5	
	7:00 AM	1:00 PM	3	
Clinical Doctor	1:00 PM	7:00 PM	3	See, evaluate and discharge the clinical patient
	7:00 PM	7:00 AM	2	
	7:00 AM	1:00 PM	2	
Pediatrician	1:00 PM	7:00 PM	2	See, evaluate and discharge the pediatric patient
	7:00 PM	7:00 AM	2	
	7:00 AM	1:00 PM	1	
Traumatologist	1:00 PM	7:00 PM	1	See, evaluate and discharge the traumatologic patient
	7:00 PM	7:00 AM	1	
	7:00 AM	1:00 PM	1	
Cardiologist	1:00 PM	7:00 PM	1	See, evaluate and discharge the cardiologic patient
	7:00 PM	7:00 AM	1	
	7:00 AM	1:00 PM	1	
Routine Doctor	1:00 PM	7:00 PM	1	Monitors and discharges the inpatient
	7:00 PM	7:00 AM	1	
	7:00 AM	1:00 PM	2	
Cashier Assistant	1:00 PM	7:00 PM	2	Closes and charges the hospital bill
	7:00 PM	7:00 AM	1	

The resources in Table 12 and their schedules are modeled on the computational model. There are particularities regarding the form of simulation in each simulation method.

4.1.6 Validation of the conceptual model

The validation of the conceptual model increases confidence in the model (BRAILSFORD et al., 2018). To summarize the information mentioned in the previous subsections, a synthesis of the conceptual model was developed, Figure 23. That will be used for the development of the computational model.

Figure 23: Conceptual model for emergency department simulation

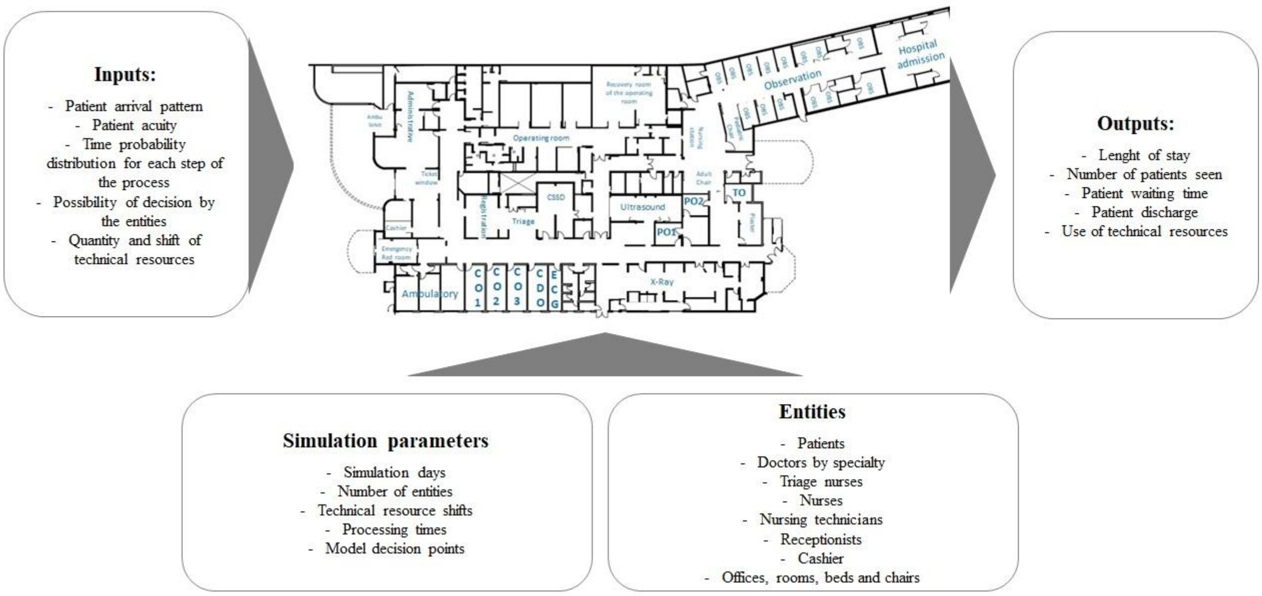


Figure 23 groups the main inputs, outputs, parameters for the simulation and entities identified in the literature and collected in the study environment. The emergency department flowchart, the main data collected, the layout and the developed conceptual model were presented to the Health Unit Administrator under study. Validation with specialists is important to ensure that patient flow follows the expected path at the time of simulation (ABDELGHANY; ELTAWIL; ABDOU, 2016; OH et al., 2016).

Table 13: Probability distribution of the times of each stage of the process

<table>
<tr><th>Operation</th><th>Probability distribution</th><th>Average (Seconds)</th><th>Standard deviation (Seconds)</th></tr>
<tr><td>T_Arrival</td><td>Log Normal (= 5.2 | = 1.3)</td><td>421,25</td><td>916,32</td></tr>
<tr><td>TW_Triage</td><td>Weibull (l = 0.64 | k = 200)</td><td>276,28</td><td>443,88</td></tr>
<tr><td>T_Triage</td><td>Weibull (l = 1 | k = 150)</td><td>153,83</td><td>154,05</td></tr>
<tr><td>TW_Registration</td><td>Weibull (l = 0.59 | k = 57)</td><td>87,22</td><td>156,03</td></tr>
<tr><td>T_Registration</td><td>Weibull (l = 0.99 | k = 170)</td><td>169,92</td><td>171,52</td></tr>
<tr><td>TW_Cardiology</td><td>Weibull (l = 0.72| k = 720)</td><td>885,95</td><td>1275,90</td></tr>
<tr><td>T_Cardiology</td><td>Exponencial (l = 0.0014)</td><td>693,15</td><td>660,90</td></tr>
<tr><td>TW_Pediatrics</td><td>Weibull (l = 0.71| k = 660)</td><td>821,72</td><td>1177,81</td></tr>
<tr><td>T_Pediatrics</td><td>Exponencial (l = 0.0014)</td><td>704,44</td><td>661,68</td></tr>
<tr><td>TW_Traumatology</td><td>Weibull (l = 0.71| k = 680)</td><td>847,55</td><td>1202,96</td></tr>
<tr><td>T_Traumatology</td><td>Exponencial (l = 0.0015)</td><td>687,99</td><td>643,40</td></tr>
<tr><td>TW_General Clinic</td><td>Weibull (l = 0.71| k = 670)</td><td>838,27</td><td>1205,38</td></tr>
<tr><td>T_General Clinic</td><td>Exponencial (l = 0.0014)</td><td>703,48</td><td>661,53</td></tr>
<tr><td>T_Bed</td><td>Log Normal (= 9.9 | = 0.75)</td><td>24989,68</td><td>18648,45</td></tr>
<tr><td>T_Chair</td><td>Log Normal (= 9.1 | = 0.62)</td><td>13687,71</td><td>13335,75</td></tr>
</table>

4.2 Computational model

The computational model is built based on the conceptual model, process flowchart and collected data. The first step is the analysis of the collected data, which needs to be prepared for entry into the simulation models. The computational model must allow the integration of simulation methods (BRAILSFORD et al., 2018).

Four simulation models were developed in the Anylogic software, discrete event simulation, agent-based simulation, hybrid simulation integrating patients in ABS and technical resources in DES and the second with the patient in DES and technical resources in ABS. In the next sections, each simulation model is explored detailing the methods used.

4.2.1 Analysis of collected data

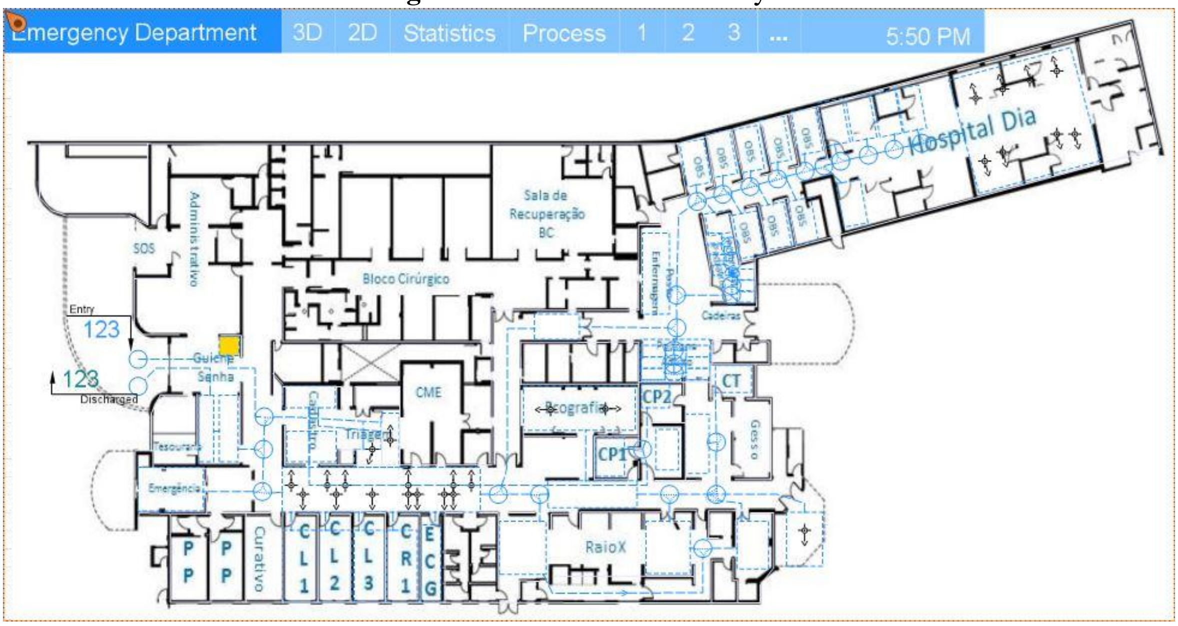
The collected data were analyzed and prepared to be included in the computational model. Firstly, as inconsistent data were identified, points outside the curve were eliminated. Data from 30 days of operation, 24 hours a day, were analyzed to find the probability distribution that most adhered to the data set, compiled in Table 13. After structured the necessary inputs for the simulation models, in the next subsections the computational models of each simulation method will be developed.

4.2.2 Development of the discrete event simulation model

Simulation of discrete events is represented by a flow diagram (LAW, 2007). The construction of the computational model, elaborated in the Anylogic software, was based on the conceptual model and the flowchart of the emergency department.

When starting the model development, the image of the layout of the emergency department was included. The patient's path was drawn above the image, the locations of the rooms, offices, and beds were identified in the software, as shown in Figure 24.

Figure 24: Simulation model layout



To facilitate the understanding of administrators, with Figure 24 3D shapes were also created for the application of an animation of the future process, thus the walls and an animation for each model entity were developed: patient, doctor, nurse, nursing technician, receptionist and cashier. Then, the necessary resources for the model and their work shifts were modeled according to the data collected in the conceptual model. In Figure 25, there is a summary of the resources created for the model.

Within each resource shown in Figure 25, the resource capacity was parameterized. If this resource has work shifts, it is linked to your registration. Finally, the location where these resources are allocated in the emergency department layout is configured. Figure 26 shows an example of the parameters of the Clinical Doctor resource.

Figure 25: DES Resources

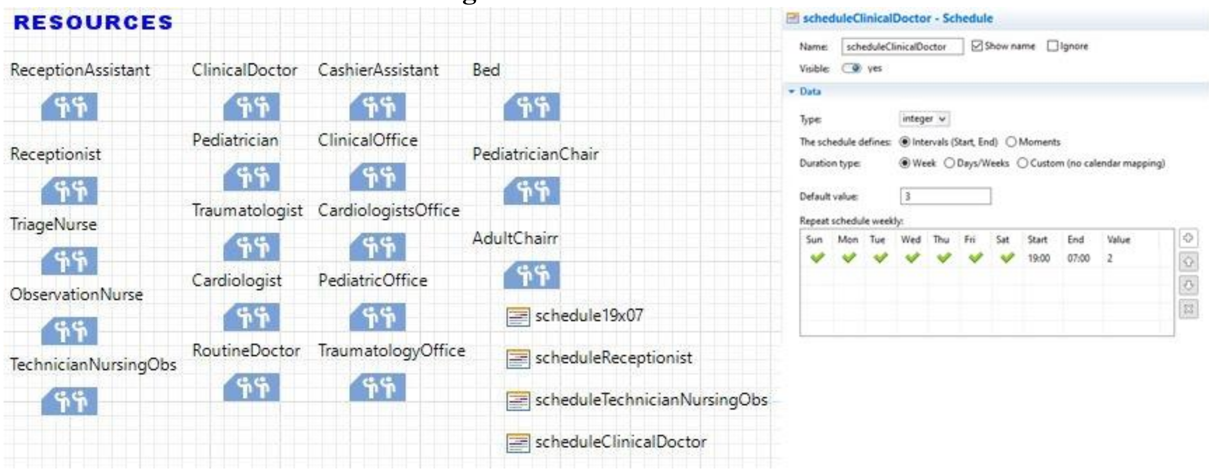
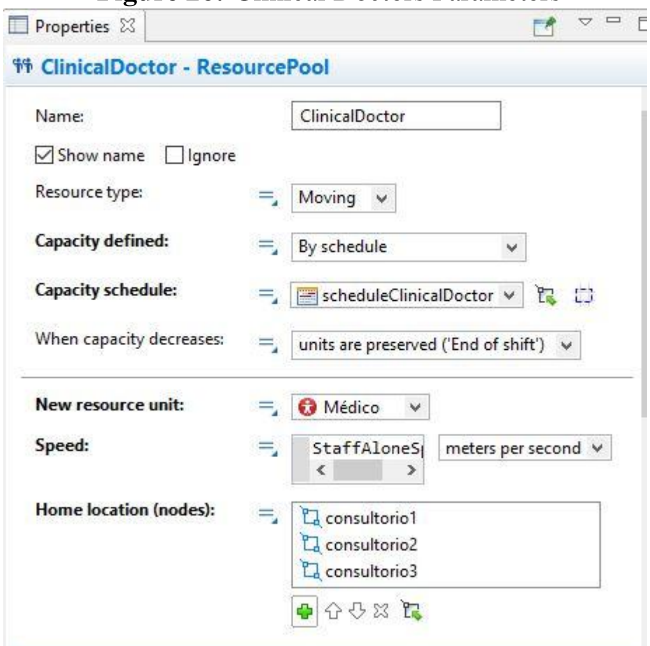


Figure 26: Clinical Doctors Parameters



Fonte: elaborado pelo próprio autor.

After the creation of the resources, the flowchart of the emergency department process is developed. The building blocks for the flow are shown in Figure 27.

With the blocks defined in Figure 27, the development of the flowchart begins, as shown in Figure 28.

Figure 27: DES Blocks

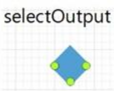
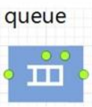
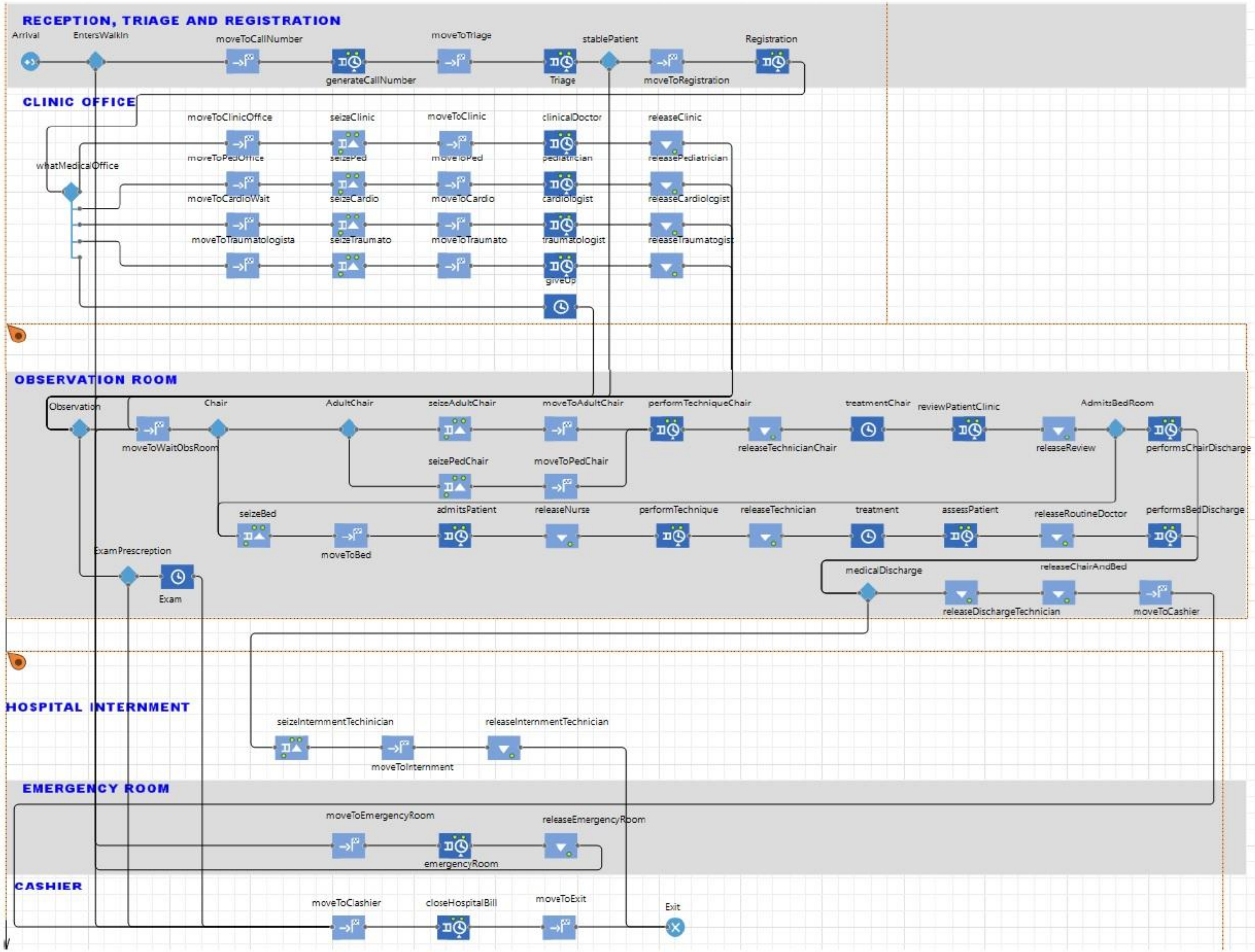
Blocks	Description	Blocks	Description
 source	It is the starting point of the flowchart, it has the function of generating entities, in this case, patients.	 sink	It is the final point of the flowchart, it discards the entities, in this case the patients.
 selectOutput	Decision point, directs the entry pacients, to one of the two exit points depending on a probabilistic or deterministic condition.	 selectOutput5	Decision point, directs the entry patients, to one of the five exit points depending on a probabilistic or deterministic condition.
 moveTo	Moves patients from one location to another in the layout.	 release	Releases a certain number of resource units used in the process previously captured by the Seize block.
 queue	A queue of patients waiting to be entered into the next block in the process flow.	 delay	It is the delay of the entity for a certain period of time, this delay can happen due to the entity, or patient in this case, going through the execution of some process.
 seize	Captures a specified number of resource units from a given ResourcePool to be used in the process.	 service	Is equivalent to a sequence Seize, Delay, Release. Capture the resource and the patient, perform a processing time and release the resource and the patient. For example, a medical consultation.

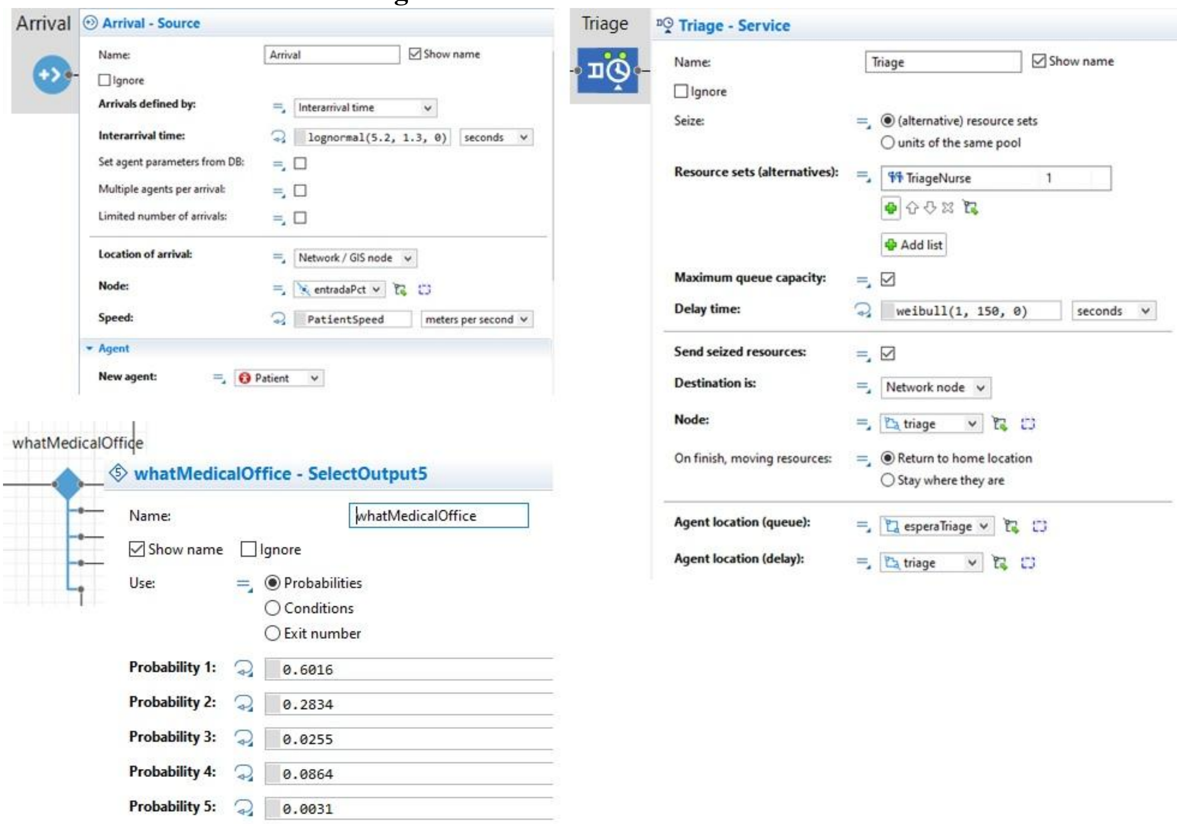
Figure 28: DES Flowchart



The connection logic among the blocks is developed according to the conceptual flowchart model. Due to a limitation in the number of resources offered in the Anylogic 8 software version Personal Learning Edition 8.4.0, the imaging exam stage was not modeled. With the completion of the flow, parameterization of the simulation model begins. The patient's arrival pattern, decision points, type and amount of resources used in each activity, and the probabilistic time distribution of each activity are included.

In Figure 29, the entry of the parameters of the three main blocks is shown: source, selectoutput and service.

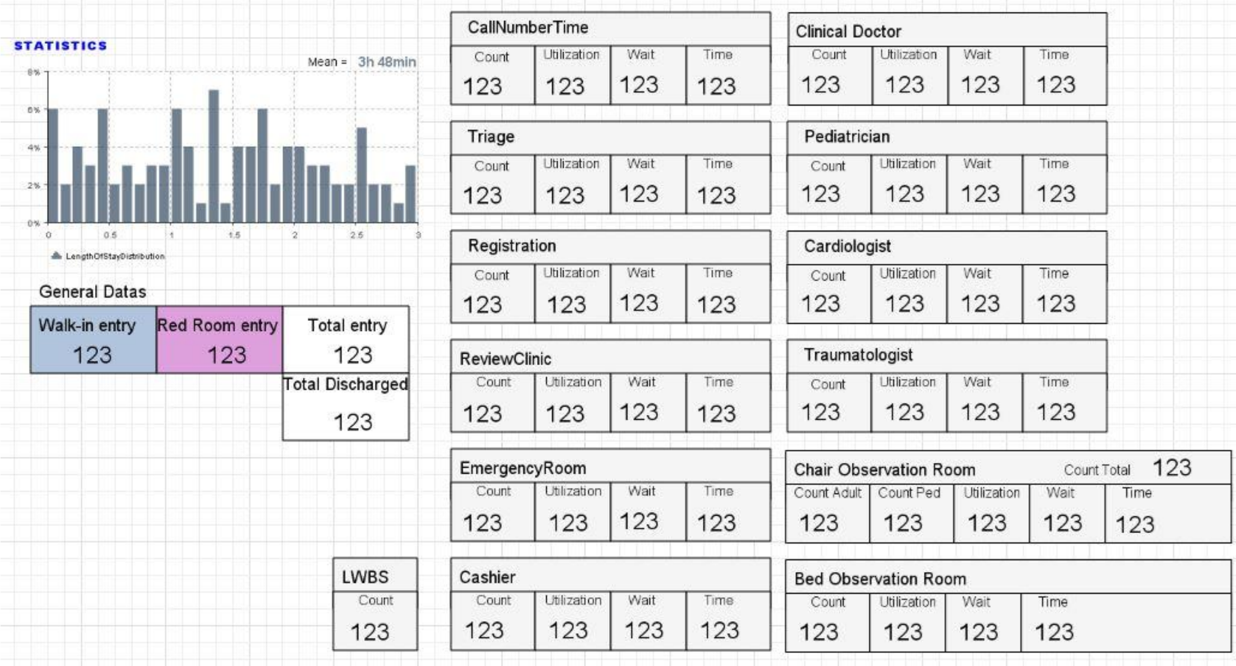
Figure 29: DES Flowchart Parameters



In the first block of Figure 29, "Source", the probability of patient arrival was included. In the "Service" block, the triage task is exemplified. This block includes the resources involved, the location where the task occurs, and the duration of the task. In the block "SelectOutput", it shows a decision point with the probability of following each flow path, in this study, what is the probability of being seen by a medical specialty.

After parameterization of the computational model, a first simulation is run to assess how the entities will behave and make the necessary adjustments. Then, a dashboard was built with the output indicators defined in the conceptual model. The dashboard is shown in Figure 30.

Figure 30: Dashboard Indicators



The indicators used are the patient's length of stay, the number of patients seen, patient waiting time at each stage, patient discharge and use of technical resources. The next Figure31, shows the settings for generating the indicators.

Figure 31: DES Parameters Indicators

Indicators of number of patients and use of resources are generated from a pre-defined command within the "Service" block, as shown in Figure 30. The patient's length of stay and waiting time indicators are generated from a system object called "Histogram Data". Within the block is included a formula exemplified in Figure 30 that records the current time and subtracts the time from the previous block.

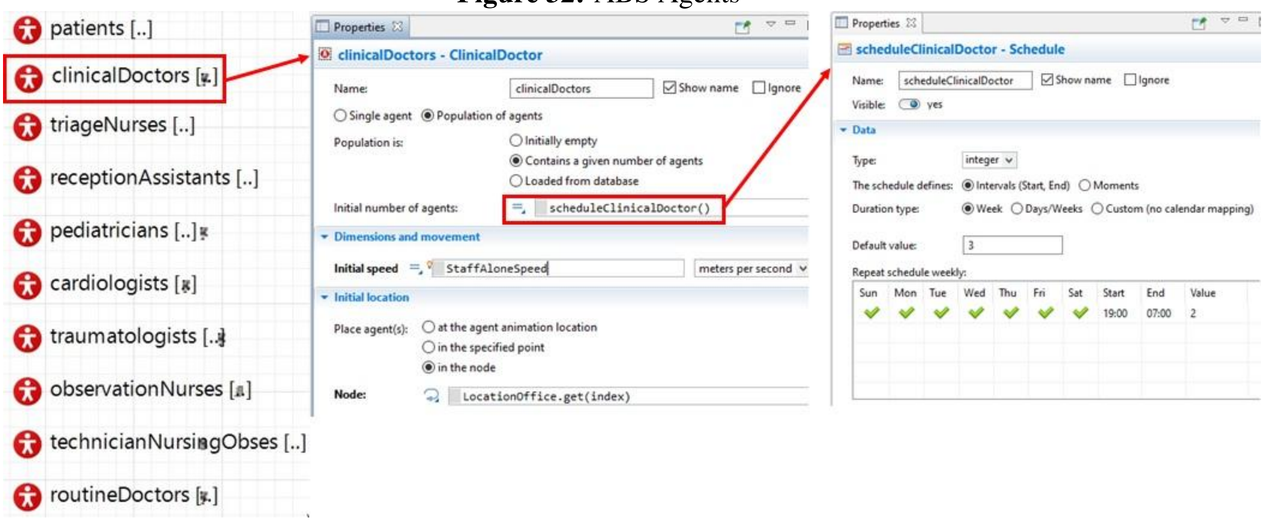
With the discrete event simulation model completed, the simulation is run to test the functioning of the indicators. Finally, the computational model must be validated as described in Subsection 4.2.6.

4.2.3 Development of the agent-based simulation model

The agent-based simulation model is interactive and adaptive, autonomous agents interact with other agents and adapt according to the evolution of their statechart (MACAL, 2016). Agents change states as they receive input. They produce outputs that influence the next state of the agent or another agent. The model is developed from the transition among states (WANG, 2009; TABOADA et al., 2011; CABRERA et al., 2011).

The agent-based simulation model starts with the layout design of the emergency department already demonstrated in Subsection 4.2.2, Figure 24. After that, the agents Patients, Clinical Doctors, Pediatricians, Cardiologists, Traumatologists, Triage Nurses, Observation Nurses, Technicians Nursing, Routine Doctors and Reception Assistants are created, as shown in Figure 32.

Figure 32: ABS Agents



In figure 32, it shows how the number of technical resources and their shifts is included. Due to the limitation of the number of agents in the Anylogic 8 software Personal Learning Edition 8.4.0, the receptionist's registration and cashier agents were not models, although, their state was included in the patient's statechart to approximate the real-time of the service As in the DES model, the imaging exam stage was not simulated.

Within each agent, their statechart is modeled. In the simulation modeling of discrete events, the model is designed inflow, in the model agent-based, it is designed thinking about the internal states of each individual. The statechart is constructed with the objects in Figure 33.

Figure 33: ABS Objects

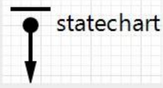
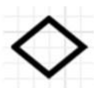
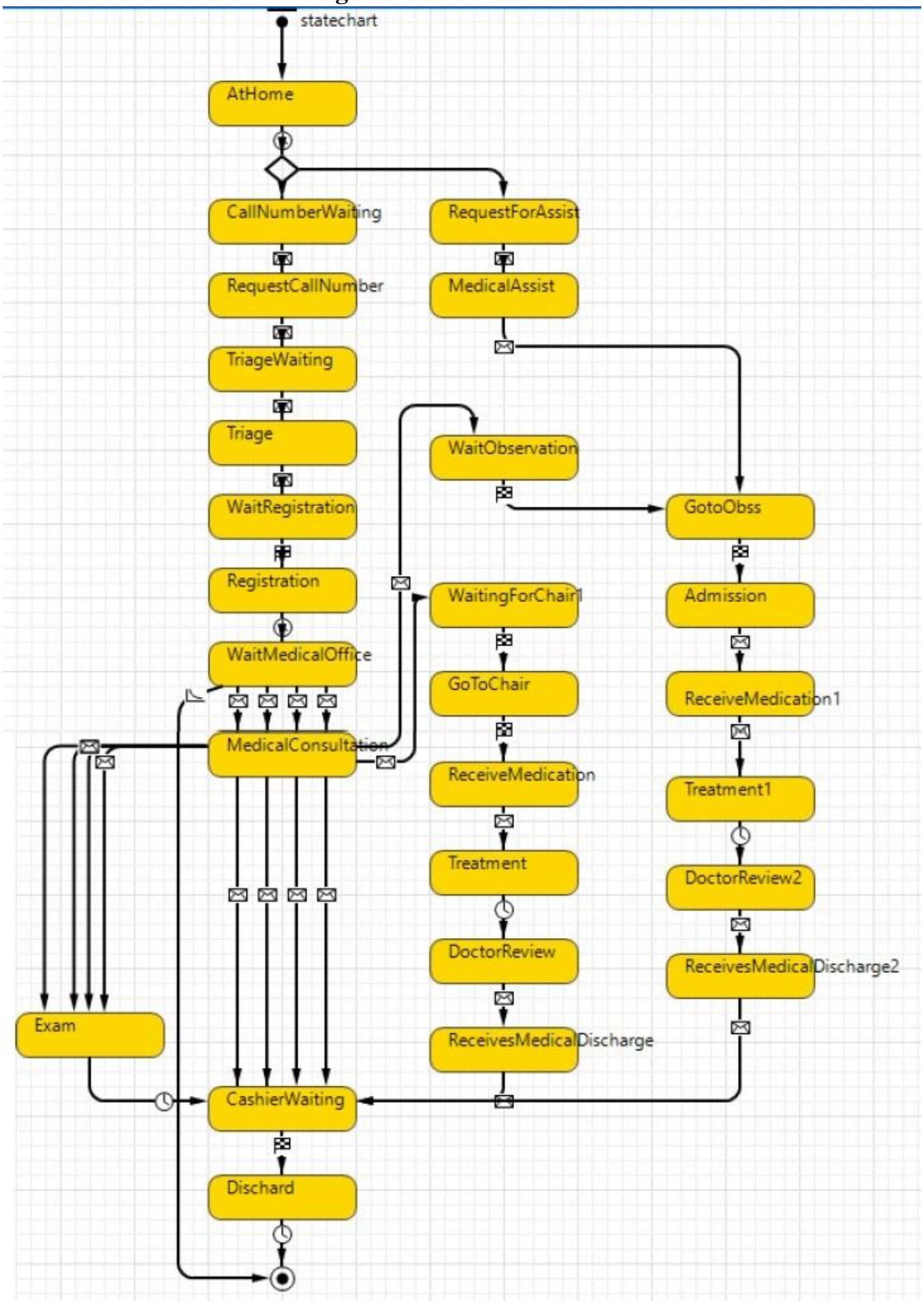
Objects	Description
	It is used to indicate the initial state of the statechart.
	The state represents the agent's condition. For example, the doctor starts in the waiting for patient state, after receiving the patient and moves to the state seeing the patient, finally to the prescription state.
	A transition indicates a change from one state to another. This transition occurs due to a timeout, rate, condition, message or arrival of the agent.
	Represents a transition branch directed the agent to more than one target state, depending on the given condition.
	It is the end point of the state chart.

Figure 34 shows the construction of the patient agent statechart. Figure 35 details the state of the other agents described as Clinical Doctors, Pediatricians, Cardiologists, Traumatologists, Triage Nurses, Observation Nurses, Technicians Nursing, Routine Doctors and Reception

The agent changes state from the "Transition" object, this object is used to change the internal state of the agent and interact with other agents. The patient's transition logic is summarized as follows:

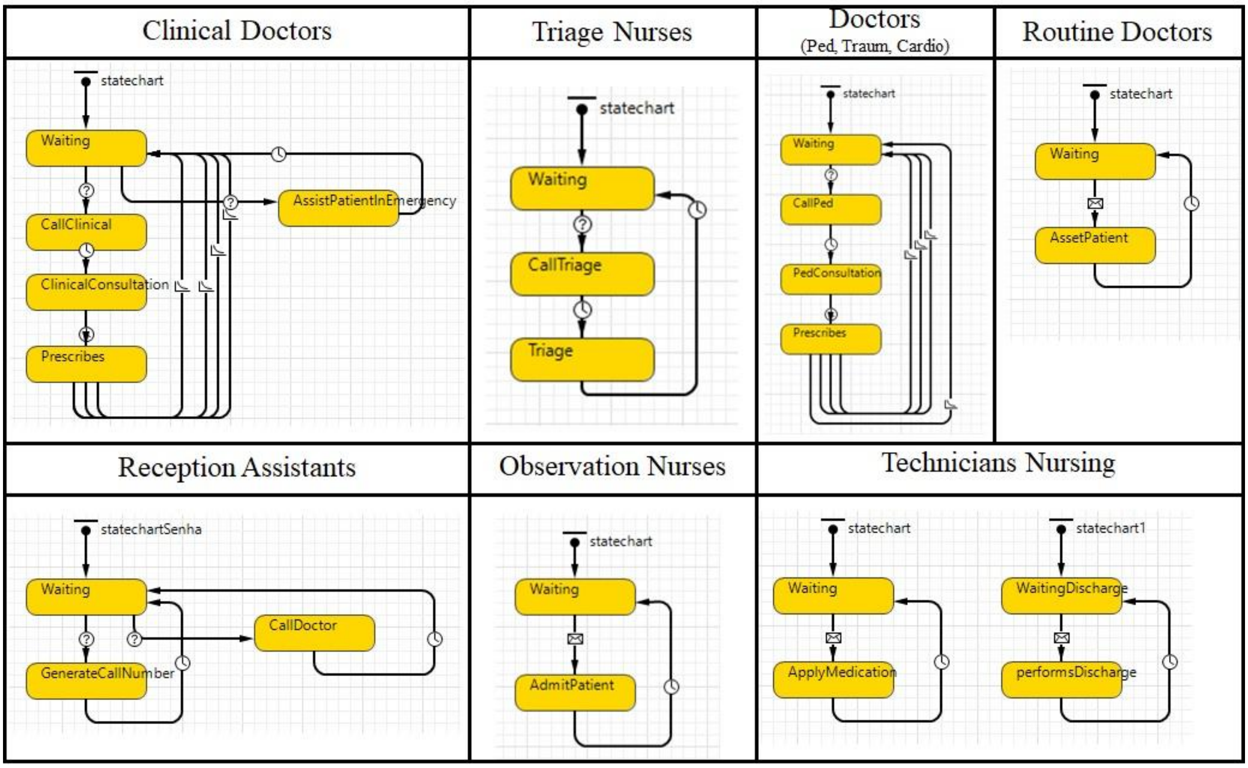
- The patient arrives at the reception, a transition sends a message to the assistant receptionist informing that there is a patient in the queue;
- If the reception assistant agent is available, it changes its status to "generating ticket number" and informs the patient agent that it also changes its status to "awaiting ticket number". When finished, the reception assistant agent sends a message to the patient informing that the "ticket number is generated";

Figure 34: Patient Statechart



- The patient moves to wait for the triage and sends a message stating that there is a patient in the queue;

Figure 35: Agents Stateschart



- The triage nurse receives the message and, being available, returns to the patient calling for triage. In the end, the triage nurse sends a message to the patient that the triage is finished and he moves to wait for the record.

- The agent for the registration area was not created, due to software limitation, so the patient only has a processing time according to real data to change to the "waiting to see a doctor" state.

- The transition informs the medical agent that there is a patient in his queue when receiving this information and being available, the doctor calls the patient through a message transition.

- When the patient arrives at the doctor, a transition in the duration of the visit occurs. After the medical agent changes to the prescription state in which a probability transition informs the patient if he goes to the observation chairs, observation beds, or is discharged.

- When receiving the information, the patient moves to the path informed by the medical agent. If discharged the patient still changes to the state of closing the hospital account that a time transition is used;

- If the patient goes to the observation the same logic of communication through messages and queues occurs with the nursing technicians, nurses, and routine physicians. Before being discharged.

The form of communication among the transitions is programmed using the Java programming language. In Figure 36, the logic of transition from a specific process step between leaving the patient's record and seeing the doctor is exemplified.

Figure 36, summarizes an agent's internal state transition configuration and communication among agents. In the image, it is also possible to observe in step 4 the inclusion of the time to visit the doctor in the "Timeout" field. The other state transitions and interactions with agents occur in the same format. The model also has objects called "variables", "probabilities" and "functions" that assist in the communication among agents and objectives called "collections" that help in the generation of agent queues.

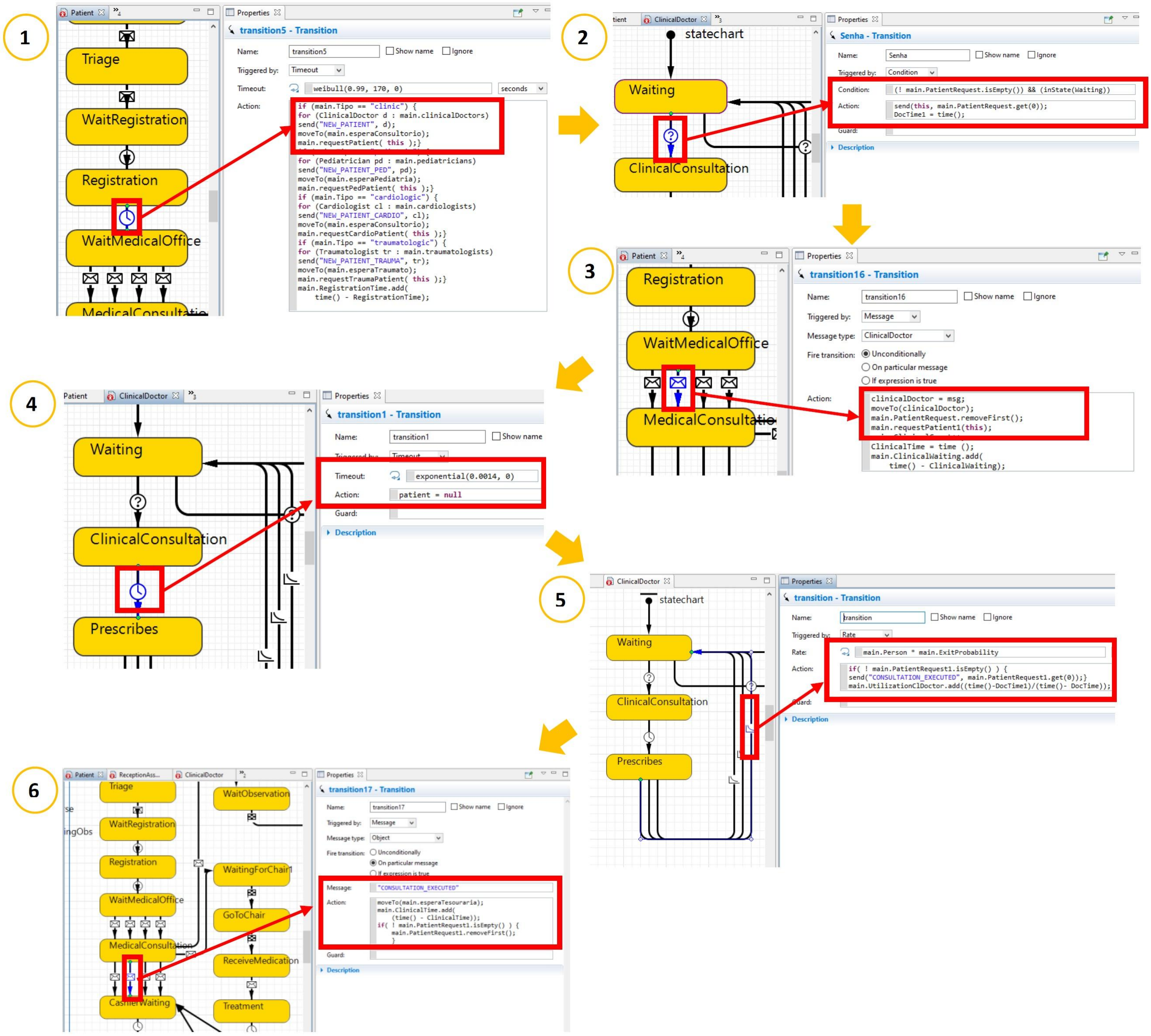
In the object, called "Event", the patient arrival rate is parameterized to start the simulation model. As shown in Figure 37, five types of events are created, one for the arrival rate of each medical specialty and one for emergency care.

After the simulation model based on agents built and programmed, a first simulation is run to assess whether the agents will behave correctly, making the necessary adjustments. As in the DES model, a dashboard was built with the output indicators defined in the conceptual model. The layout and outputs of the dashboard are the same as previously shown in Figure 30, in subsection 4.2.2. However, the way to collect the results in the ABS model is different from the DES model, as shown in Figure 38

The number of patient indicators is defined by a variable that counts the number of patients who pass through the "Triage" state. The use of resources is generated calculated by a formula that subtracts the time occupied by the total time of the resource. The length of time and waiting time indicators are generated from an object of the system called "Histogram Data", within the states of the patient that records the waiting time and the activity time.

With the agent-based simulation model completed, the simulation is run to test the functioning of the indicators and adjust them if necessary. Finally, the computational model must be validated as described in Subsection 4.2.6.

Figure 36: SBA Transition



4.2.4 Development of the hybrid simulation model modeling the patient in ABS and the resource in DES

Hybrid simulation is a combination of two or more methods. In this section, the ABS methods were combined to model the patient's behavior and the DES method to model the flow of the resource. Similar studies were done by Hagtvedt et al. (2009) e Anagnostou, Nouman e Taylor (2013), although, both authors simulated the behavior of ambulances in

Figure 37: Arrival rate - Event

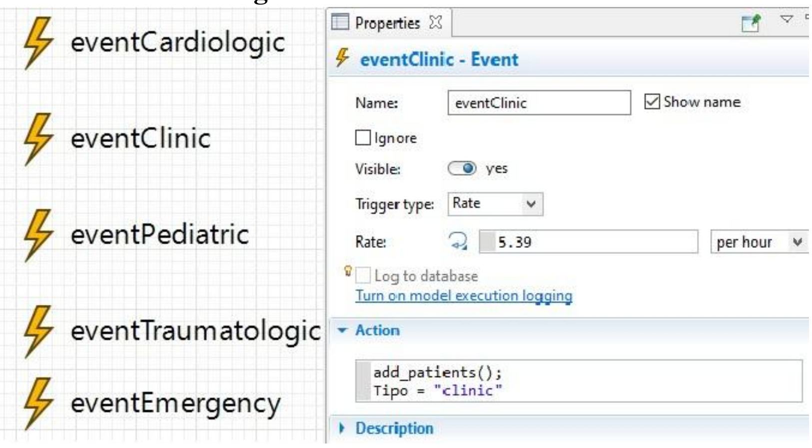
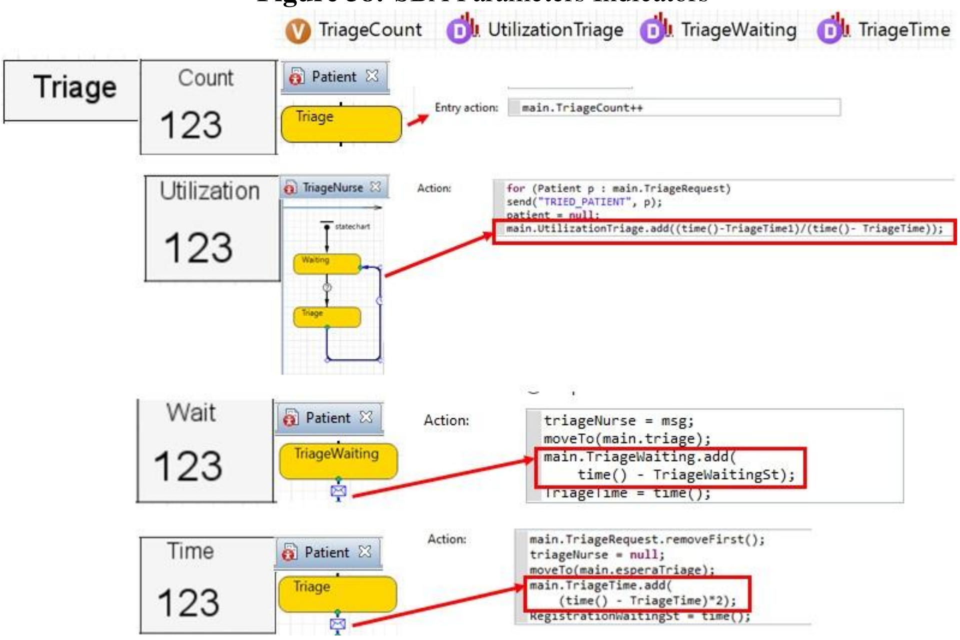


Figure 38: SBA Parameters Indicators

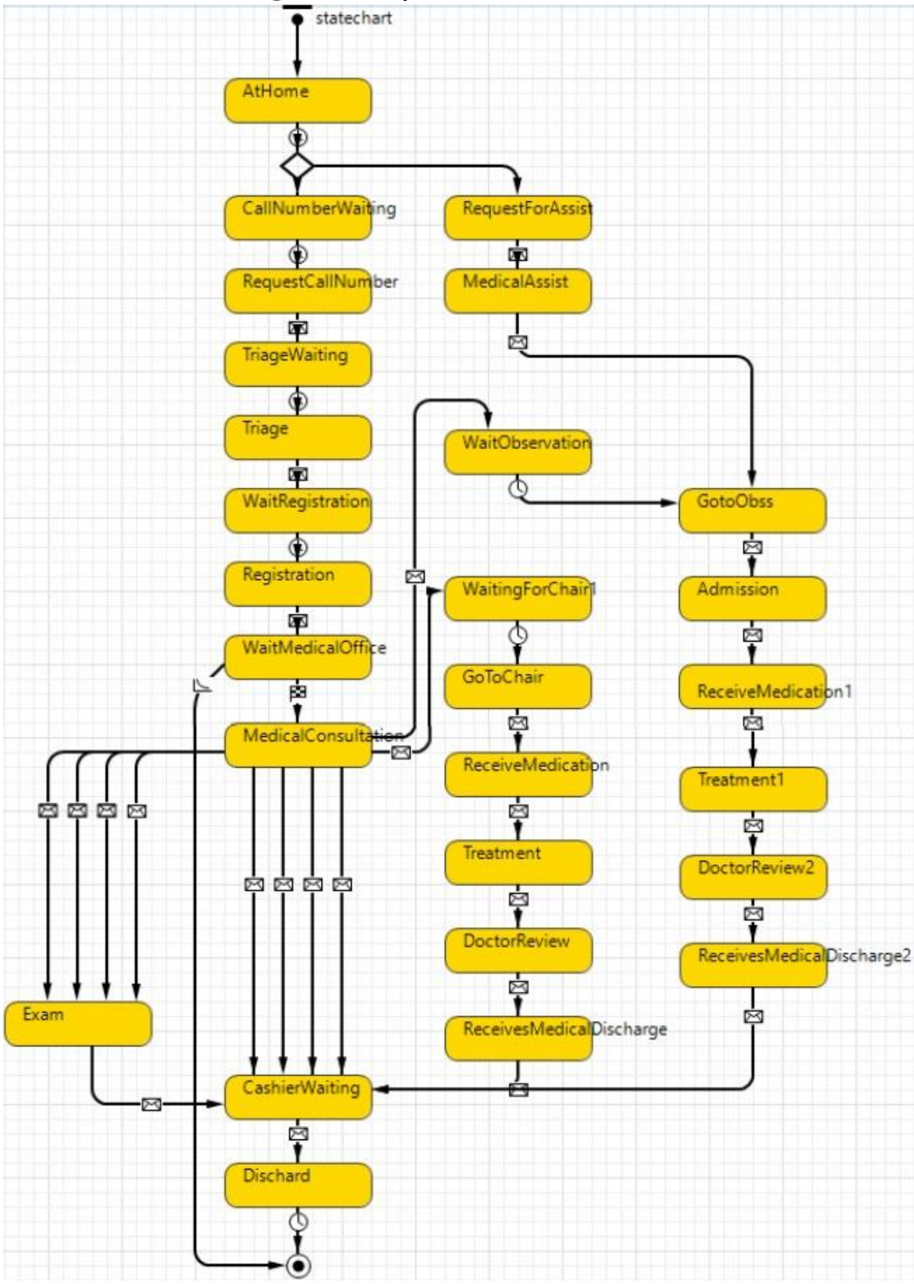


ABS and the flow of the emergency department with DES.

The Anylogic software allows to integrate different simulation methods, thus, the flows, resources, agents and statecharts already developed in subsections 4.2.2 and 4.2.3 are replicated for the hybrid models. However, the communication and integration settings among the methods are new in this section. The layout of the emergency department kept the same configuration and design as the previous methods.

To start the computational model of this method, the same resource parameters of the DES method were copied, already described in subsection 4.2.2, Figure 25. A patient agent statechart was also used, very similar to the one developed in the subsection 4.2.3, Figure 34. However, there are some changes in the transition objects that change due to the integration with the DES model described later. Figure 39 shows the statechart of the patient agent.

Figure 39: Hybrid Statechart Patient



The flowchart of discrete events used for the resources is similar to that used in Figure 28, but without the connection lines of the entities that represented the patients, because in this case the patient agent, model in ABS, was used. To connect the two models, the objects

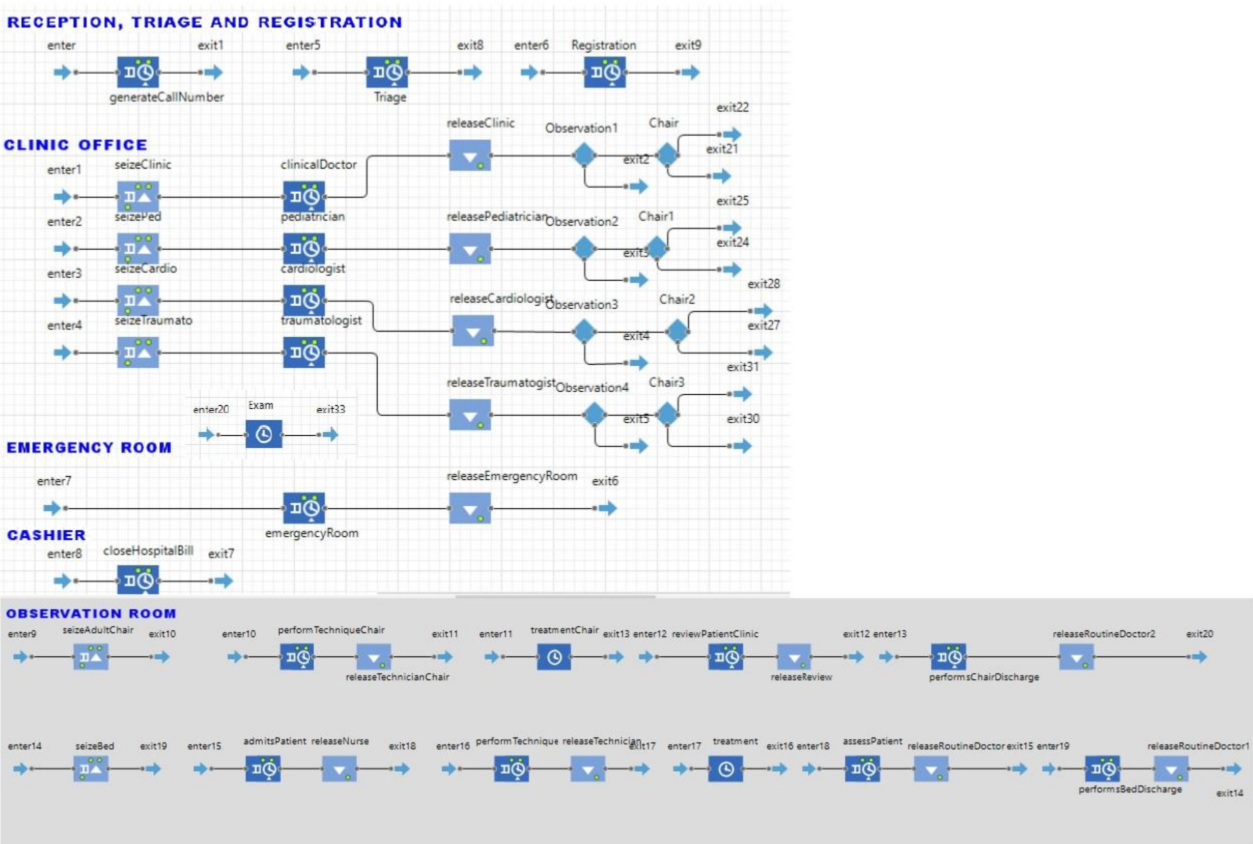
"Enter" and "Exit" explained in Figure 40 were used.

Figure 40: Objects Conection

Objects	Description
enter	Inserts the (already existing) agents into a particular point of the process model.
exit	Takes the incoming agents out of the process flow

The resource flowchart was adjusted using the connection objects in Figure 40. The resource flowchart is shown in Figure 41. After the patient's statechart is adjusted in Figure

Figure 41: Resources Flowchart



39 and the flow of resources is adapted according to Figure 41 the way of integration between

the two models is programmed. The communication starts with the patient's transition logic modeled in ABS, summarized as follows:

- The patient arrives at the reception, his internal state changes and a transition sends the patient agent from code, using the "Enter" object, to the ticket number generation flow in discrete events;
- The ticket number generation step occurs through a "Service" block with a registered activity time and resource allocation, after the activity time ends, the patient leaves via the "Exit" object;
- The "Exit" object sends a message to the patient agent stating that the ticket number is generated, which upon receiving the message changes its internal state to the next state. The patient moves to wait for the triage and resends the patient agent to the flow of the triage resource using "Enter";
- After completing the processing time of the triage, it sends an "Exit" message informing that the patient agent is triaged;
- Thus, all other patient states and resource flows occur. Going through medical care according to specialty, through decision points whether the patient will be referred to the observation chairs, observation beds, or discharged, triggering the flow of resources.

In Figure 42, the integration among the states of completion of the registration until the conclusion of the clinical medical visit is detailed. Communication among transitions is developed using the Java programming language. In Figure 42, the integration between the two methods is exemplified.

To start the simulation model, the same logic as the ABS model is used, including the objects called "Event" with the parameterization of the patient arrival rate as shown in Figure 37 of Subsection 4.2.3. Five types of events are created, one for the arrival rate of each medical specialty and one for emergency care. Based on the built-in hybrid simulation model, tests are run to assess the model's behavior and make adjustments. In the sequence, the dashboard screen is developed, as shown in Figure 30, in subsection 4.2.2.

The indicators of the patient's length of stay and the number of patients arriving and discharging are collected from a formula inserted in the patient's states as shown in Figure 43.

The results of the indicators for each step of the flow, such as the number of patients in each step, utilization, waiting time and time for each activity are collected according to Figure 31 of Subsection 4.2.2.

Figure 42: Hybrid ABS/DES Transition

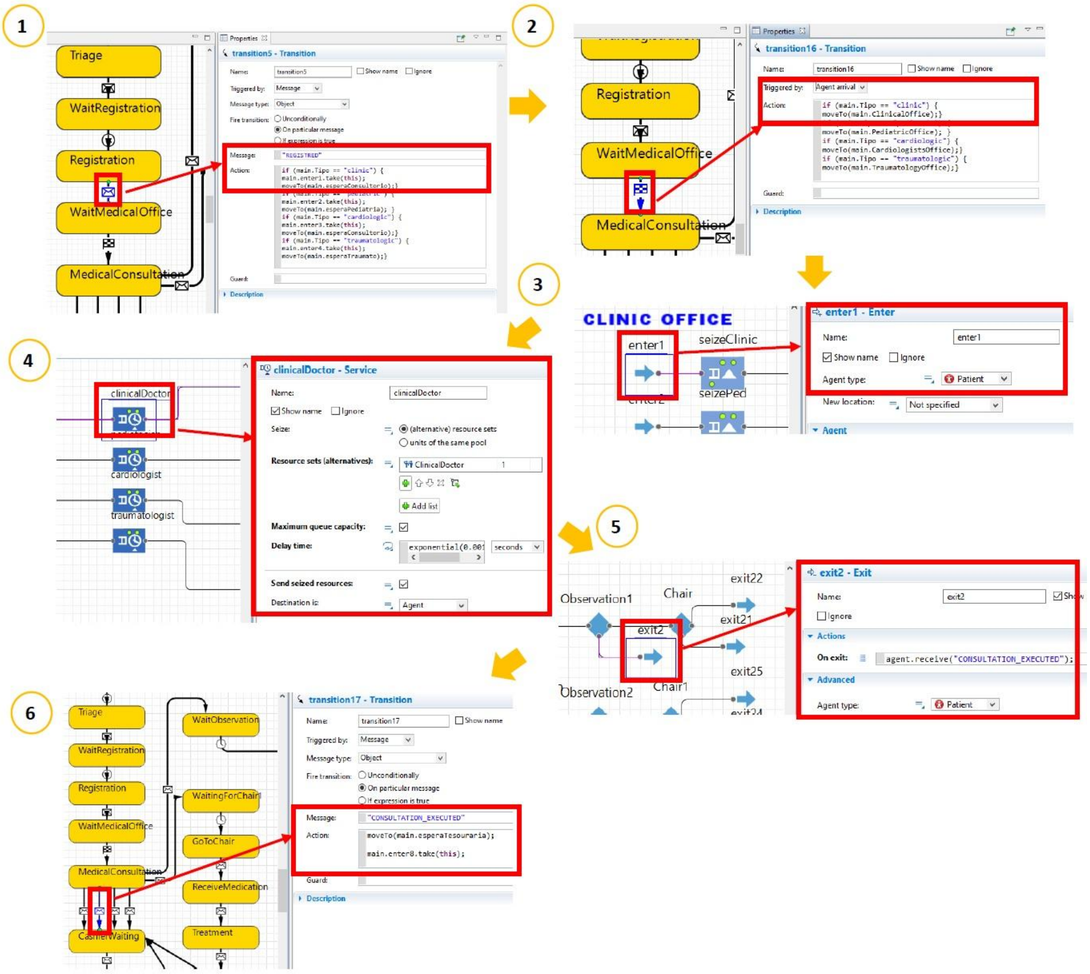
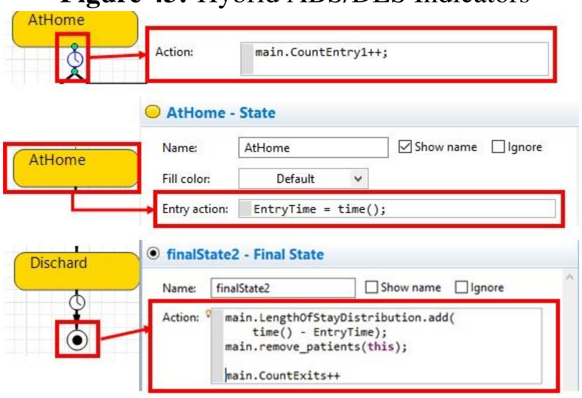


Figure 43: Hybrid ABS/DES Indicators



After completing the hybrid modeling integrating the ABS methods to model the patient's behavior and the DES method to model the flow of the resource, the simulation is run to test the functioning of the indicators. Finally, the computational model must be validated as described in Subsection 4.2.6.

4.2.5 Development of the hybrid simulation model modeling the patient in DES and the resource in ABS

In this subsection, the DES methods to model the patient flow and the ABS method to model the behavior of the resource were combined. Similar studies have been done by Mackay et al. (2013) and Abdelghany, Eltawil e Abdou (2016).

As described in Subsection 4.2.4, this subsection will also use the flows, resources, agents, and statechart already developed in subsections 4.2.2 and 4.2.3. However, configurations and integrations will be developed to build a model integrating DES for patients and ABS for resources. The layout of the emergency department kept the same configuration and design as the previous methods.

To start the computational model of this method, a patient flowchart was created, very similar to the one developed in subsection 4.2.2, Figure 28. However, for this method, the "Services" blocks were replaced by "Queues" and "Delay" blocks, already described in Figure 27, This action occurred, as the time settings for activities and resources were deleted, as shown in Figure 44, as these will be modeled in ABS.

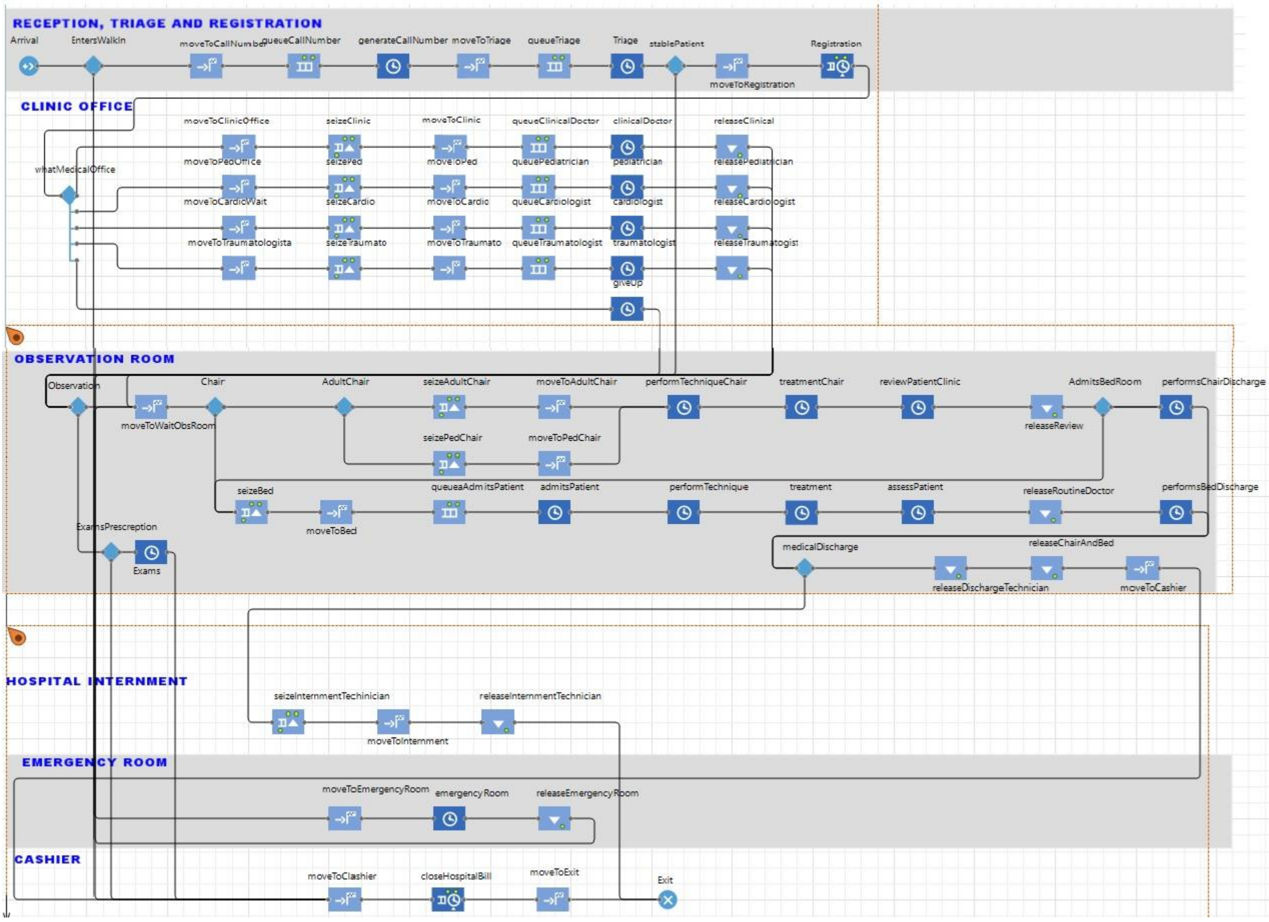
To model the resources in ABS, the statechart of each agent, except the patient, were used, similar to the statechart shown in Figure 4.2.3 and Figure 34. However, the transition objects are modified, due to the way of integration with the DES model. The integration flow is summarized as follows:

- Patient advances in the flow to the ticket number generation block, at that moment the block sends a message requesting the generation of ticket number to the reception assistant agent;

- If the reception assistant agent is available, it changes its state to "generating ticket number". The processing time starts and in the end, the reception assistant agent sends a "stopDelayForAll" command to end the time of the ticket number generation block and changes its state again to wait;

- Upon receiving the command "stopDelayForAll" the patient follows the flow to the waiting triage stage. Upon reaching the triage stage, the triage block sends a message to the triage nurse agent that changes its state to triage, in the end, it sends the command to end the triage block at DES;

Figure 44: Patient Flowchart



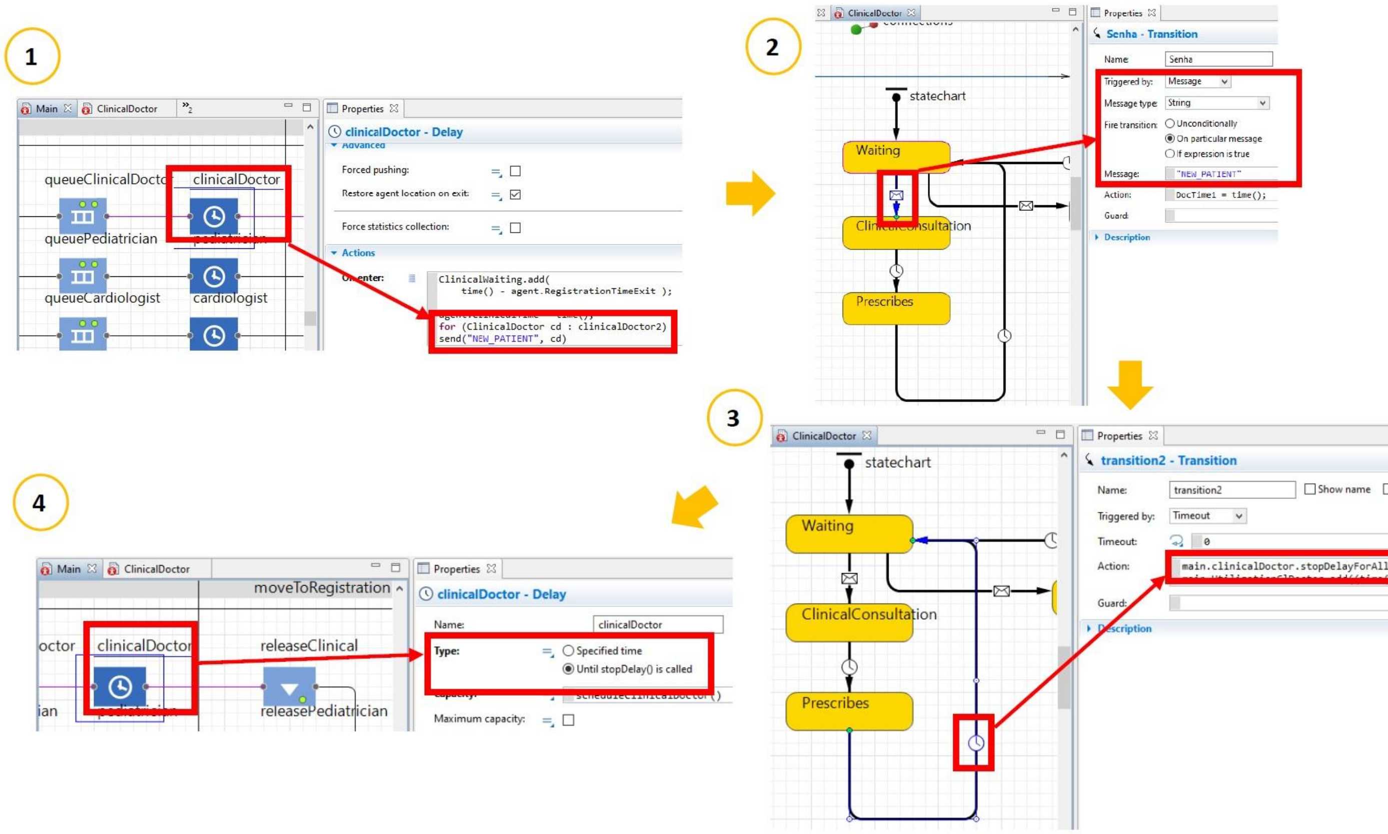
- In this sequence, the patient follows the flow of discrete events, all other resources are modeled on agents, passing through the physician according to specialty, through the decision points whether the patient will be referred to the observation chairs, observation beds or discharged, triggering the others resources;

- In this model, the decision points are probabilistically determined by the flow of discrete events. For example, if you will be sent for observation or discharge.

Figure 45 shows the way of integration between the two methods, the stage of consultation by the clinical doctor is exemplified. Communication among transitions is developed using the Java programming language. In Figure 45, it is possible to observe the command "stopDelayForAll", that when the activity block is activated, it is programmed to stop and release the patient in the flow.

To start the simulation model, the same logic as the DES model is used, which includes the

Figure 45: Hybrid DES/ABS Transition



probability of arrival of patients in the "Source" block, according to Figure 29 of Subsection 4.2.2. Specialties are divided after the triage stage from a decision point in the flow.

With the built-in hybrid simulation model, tests are run to assess the model's behavior, making adjustments. In the sequence, the dashboard of indicators is developed as shown in Figure 30, in Subsection 4.2.2. The indicators length of stay of the patient, number of arrival and discharge of patients number of patients entering each stage are collected from a count command in the DES model in the same way used in Figure 31, in Subsection 4.2.2. The results of the indicators of resource utilization, waiting time and time of each activity within the resources are collected as shown in Figure 38 of Subsection 4.2.3.

Completed the hybrid simulation model integrating the DES methods to model the patient flow and the ABS method to model the behavior of the resource, the simulation is run to test the functioning of the indicators. Finally, the computational model must be validated as described in Subsection 4.2.6.

4.2.6 Validation of computational models

The validation of the computational model is an important step for the quality of the simulation (SARGENT, 2005). First, a visual inspection of the patient's path was conducted and then a statistical validation comparing the simulated results with the actual results. These steps were also applied in the study researched by Abo-Hamad e Arisha (2013) and Oh et al. (2016). For the visual inspection, the layout of the emergency department, the patient's path, and a 2D and 3D animation according to Figure 46 were developed for all modeled methods.

Figure 46: Visual Validation (2D/3D)

Statistical validation compared the patient's length of stay indicators according to Abdelghany, Eltawil e Abdou (2016), number of patients, time of activity and waiting for triage stages, registration and to see the doctor with the results shown in Table 10.

15 replications of each of the four simulation methods were run. The simulation parameters were for 30 days for warming and after another 30 days with the parameters defined in Subsection 4.2.1. Inconsistencies were identified in the chair and bed observation times in all methods, which was impacting the length of stay. Thus, fine-tuning adjustments were made in chair and bed observation time to approximate real times.

When identifying that most of the real data were within the confidence intervals, mainly arrival rate and length of stay, the validated process in each method was considered. The results are shown in Table 14. Also, the results and visual animation of each model were presented for validation by the Health Unit Administrator. In the next subsection, the results generated are analyzed and compared with the theoretical background and among each method.

4.3 Comparison and assessment of the results

When validating the computational model, the 15 replications for each simulation method were used to statistically analyze the adherence among the simulation methods. The results are shown in Table 14. Sixteen results were analyzed in comparison with the real time and with the time of the four method. These methods enabled validation of the number of patients entering, the time spent in chairs, length of stay in observation beds, and the total time in the Emergency Department.

In general, the results of the DES method were the only ones that all lay within the confidence intervals. Due to the characteristic of system flow and queues with passive entities in the DES method, it presented greater ease of modeling and configuration of inputs, thus generating more stable results, as stated by Law (2007); Siebers et al. (2010); Abdelghany, Eltawil e Abdou (2016)

The ABS method showed the highest number of results outside the confidence intervals. In total, there were six, all below the real time, even with the service time within the parameters. Most of them represented by the patients' waiting times: for screening (triage); and to see clinical, pediatric, cardiological and traumatological doctors. These results demonstrate the difficulty of modeling queues in the ABS method

The results generated by the ABS method that were within the confidence intervals also showed greater variation compared to real time and other methods. The ABS model demonstrated greater ease of modeling in the observation chairs and beds steps, in which there were more interactions among the doctor, nurse, technician and patient, and where the concept of the queue was not applied. These results are in line with Siebers et al. (2010) and Macal (2016) who described that the focus is not on the concept of queues, but the interaction among individuals.

The hybrid DES / ABS method, which models the integration of the patient flow in DES with the resources in ABS, had four results below the real time: the waiting time to see a clinical, pediatric, cardiological or traumatological doctor. As this method used the same

Table 14: Comparison of simulation results

Methods/Data	**Arrival**					**Wait triage**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	12842	12827	25,047	12757	12896	4,60	4,63	0,01	4,60	4,67
ABS	12842	12917	32,237	12828	13007	4,60	**4,09**	**0,02**	**4,04**	**4,15**
DES/ABS	12842	12092	718,310	10098	14087	4,60	4,43	0,14	4,03	4,83
ABS/DES	12842	12931	35,040	12834	13029	4,60	**3,12**	**0,04**	**3,00**	**3,24**
Methods/Data	**Time triage**					**Wait registration**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	2,567	2,58	0,0067	2,56	2,60	1,45	1,45	0,0032	1,44	1,46
ABS	2,567	**1,14**	**0,0044**	**1,12**	**1,15**	1,45	1,45	0,0033	1,44	1,46
DES/ABS	2,567	2,42	0,1097	2,11	2,72	1,45	1,66	0,1352	1,28	2,03
ABS/DES	2,567	2,58	0,0059	2,56	2,59	1,45	1,47	0,0599	1,31	1,64
Methods/Data	**Time Registration**					**Wait Clinical**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	2,833	2,83	0,0077	2,81	2,86	13,971	13,83	0,1109	13,52	14,14
ABS	2,833	2,84	0,0043	2,83	2,85	13,971	**12,76**	**0,3698**	**11,73**	**13,79**
DES/ABS	2,833	3,59	0,7454	1,52	5,66	13,971	**12,15**	**0,1369**	**11,77**	**12,53**
ABS/DES	2,833	2,84	0,0072	2,82	2,86	13,971	13,09	0,4312	11,89	14,29
Methods/Data	**Time Clinical**					**Wait pediatritian**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	11,73	11,82	0,0368	11,72	11,93	13,695	13,67	0,1583	13,23	14,11
ABS	11,73	11,81	0,0604	11,64	11,98	13,695	**12,04**	**0,2036**	**11,47**	**12,60**
DES/ABS	11,73	11,84	0,0593	11,67	12,00	13,695	**12,64**	**0,1470**	**12,23**	**13,05**
ABS/DES	11,73	**11,85**	**0,0380**	**11,74**	**11,95**	13,695	13,40	0,3207	12,51	14,29
Methods/Data	**Time pediatritian**					**Wait cardiologist**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	11,74	11,87	0,0663	11,69	12,05	14,765	15,32	0,5931	13,67	16,97
ABS	11,74	11,76	0,0534	11,61	11,90	14,765	**11,13**	**0,4237**	**9,95**	**12,30**
DES/ABS	11,74	11,92	0,0650	11,74	12,10	14,765	**12,24**	**0,2560**	**11,53**	**12,95**
ABS/DES	11,74	11,93	0,0703	11,73	12,12	14,765	13,88	0,4390	12,66	15,10
Methods/Data	**Time cardiologist**					**Wait traumatologist**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	11,55	11,85	0,1426	11,45	12,24	14,126	14,29	0,1472	13,88	14,69
ABS	11,55	11,75	0,1951	11,21	12,29	14,126	**12,32**	**0,2763**	**11,56**	**13,09**
DES/ABS	11,55	11,83	0,2582	11,11	12,55	14,126	**11,75**	**0,1906**	**11,22**	**12,28**
ABS/DES	11,55	11,61	0,1375	11,23	11,99	14,126	13,77	0,3594	12,78	14,77
Methods/Data	**Time traumatologist**					**Time Chair Observation**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	11,47	11,62	0,1080	11,32	11,92	273,52	271,56	1,2950	267,96	275,15
ABS	11,47	11,19	0,1015	10,91	11,47	273,52	273,00	1,7280	268,21	277,80
DES/ABS	11,47	11,32	0,0927	11,06	11,58	273,52	271,37	1,5109	267,17	275,56
ABS/DES	11,47	11,63	0,0697	11,43	11,82	273,52	272,86	1,1834	269,57	276,14
Methods/Data	**Time Bed Observation**					**Length of stay**				
	Real	Average	Standard error	Lower limit	Upper limit	Real	Average	Standard error	Lower limit	Upper limit
DES	478,3	474,11	2,3704	467,52	480,69	226,33	227,58	0,6953	225,65	229,51
ABS	478,3	481,49	4,0643	470,20	492,77	226,33	234,04	3,9873	222,97	245,11
DES/ABS	478,3	481,68	2,6959	474,19	489,16	226,33	227,21	0,6266	225,47	228,95
ABS/DES	478,3	477,60	2,1601	471,60	483,59	226,33	223,92	5,1608	209,59	238,25

Table 15: Time for running the simulation

Methods	Time (min)
DES	2,525
ABS	24,135
DES/ABS	1,826
ABS/DES	3,686

interaction modeling used for the resources in the ABS method, the same problem occurred with the results of the model's waiting times in ABS. The screening (triage) times were stabilized in this method, possibly due to the low number of interactions of the screening (triage) resource and the communication format with the patient's flow in DES.

The ABS / DES method that models the patient's behavior in ABS and the resources in DES, presented only one point below the real time, the waiting time for screening (triage). However, it also showed a point above the real time, the visit time of the clinical doctor, although it was very close to the real time. The model has more stable steps, as the resources were modeled in DES. Possibly, the variation between the two results occurred due to the communication format between the ABS model of the patient's behavior and the DES model for the flow of resources.

When simulations were run, the Anylogic software also recorded the run times for each model. Table 15 shows the times in minutes to generate the 15 replications of each method. From the results in Table 15, it can be seen that the model that demonstrated the worst performance in simulation speed was the ABS model, due to the level of details, interactions, and quantity of programming codes. The second slowest simulation was that of the ABS/DES method that uses the patient flow in ABS, but the time was less compared to the ABS-only method, which was reported in the Abdelghany, Eltawil e Abdou (2016) description stating that the purely ABS model takes more time due to the need for details. Therefore, the simulation of the method only in DES has a better performance. The fastest simulation was the DES / ABS method, which further reduces the processing time.

It is also possible to compare the quality of the simulation models for 2D and 3D visual animation. They were better represented in Hybrid methods and DES. The ABS model had difficulty in visually representing waiting flows. The ABS method also demonstrated a great need for data, knowledge of the environment, and programming codes, whereas the hybrid models only used programming codes to integrate methods. Finally, the DES model was the one that least needed knowledge about the environment and programming codes.

The results of the comparison of the modeling and running of the four emergency

Table 16: Methods vs resources requirements

Methods \Resources	Time (months)	Money	Knowledge	Data
Discrete Events Simulation	1	$	>=Moderate	>=Some raw data
Agent Based Simulation	3	$$$	Complete	All type
Hybrid: Simulated ABS Patient and simulated DES Resources	2<t<3	$$<m<$$$	>=Expert	>=Good data
Hybrid: DES simulated Patient and simulated ABS Resources	2<t<3	$$<m<$$$	>=Expert	>=Good data

department simulation methods are evaluated. Based on the metrics, Table 8 described by Naseer, Eldabi e Young (2010) and Jun et al. (2011) and the author's experience in developing the four models in the Anylogic software, Table 16 was developed, which summarizes the need for resources for the development of each method.

According to Naseer, Eldabi e Young (2010) and Jun et al. (2011), the comparison criteria among the simulation methods were time, cost, knowledge and data. The DES method, because it has a concept of flow and pre-defined steps, as described by Law (2007) and Denton (2013), has simplified modeling compared to the other methods. The low level of interaction among the entities reduces the amount of programming, making the simulation processing time faster than the others. According to Günal e Pidd (2010), the level of details of the model also impacts the time for development of the model.

The cost to develop the DES model was also the lowest considering the rate per hour. Knowledge about the problem and its implications is moderate, and the necessary data is raw. Knowing the problem is important to understand what is being looked for, although its implications for the model's behavior and the interactions among the entities are basic, needing knowledge of the steps of the process, the quantity of resources, the duration of the activities, and the main decision points, for example, how many patients are admitted for observation.

In the ABS method, the behavior and interaction of patients and the main resources were modeled individually. The adaptive model, according to Macal (2016), allows agents to interact with others, changing their behavior throughout the simulation. Because of this, the complexity of development and the level of configuration increase, requiring Java programming language, thus generating more time and cost for creation and processing of the simulation. Knowledge and the demand for data need to be complete, as agents act in a behavioral manner. In this case, to model the emergency department, it is necessary to observe the movements, reactions and interactions of patients and resources, as detailed in Subsection 4.2.4.

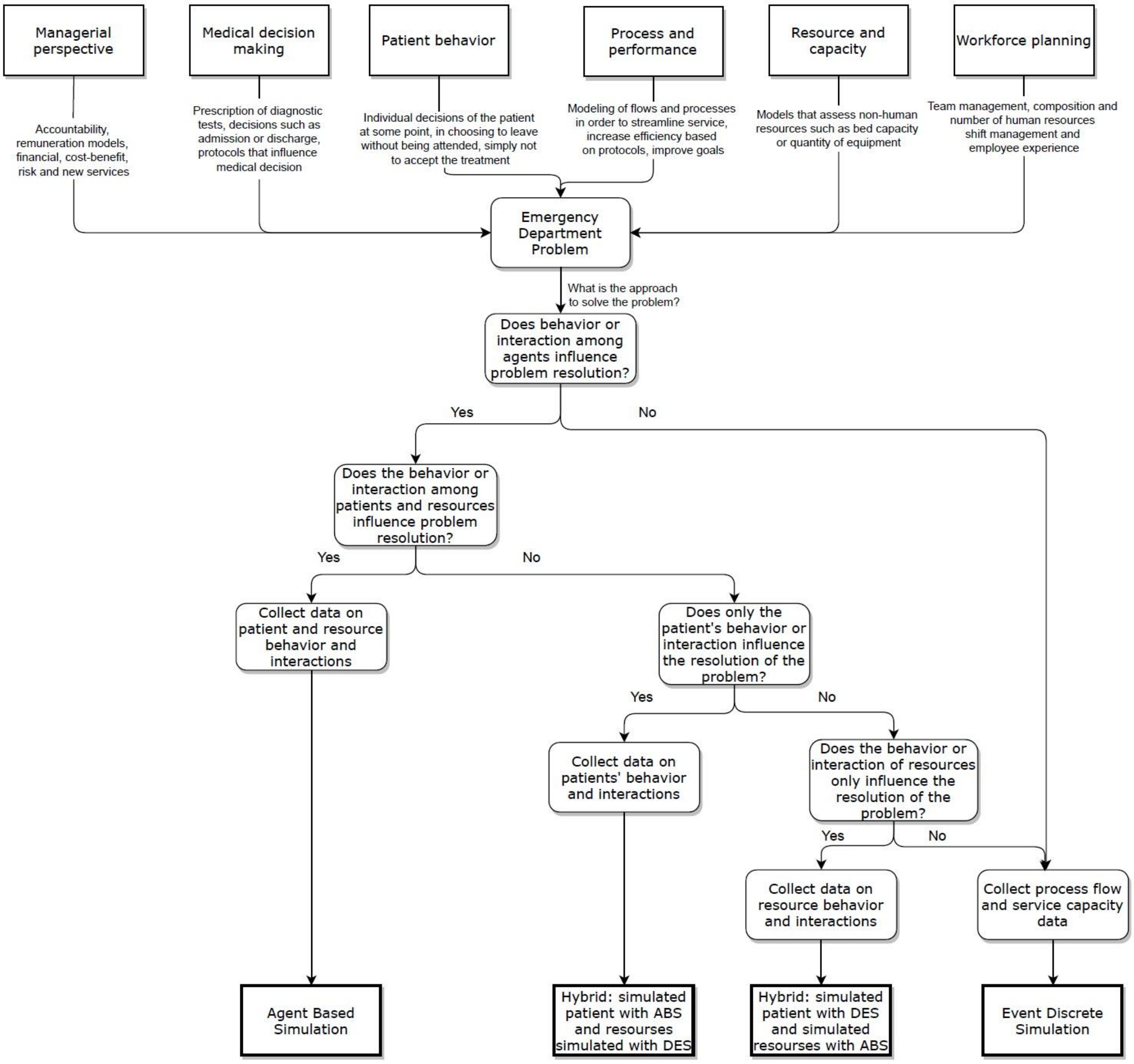
The hybrid methods used in this study integrate the DES and ABS methods in the same model, according to Brailsford et al. (2018). In both integrated models, the development time was shorter than the development time of the ABS-only method, since both the DES model and the ABS model had already been developed, and it was only necessary to create the integration logic between both. However, when developing the model from the beginning, hybrid methods tend to take longer than just DES, but are faster than just ABS. In this method, only the agents‘ statecharts were modeled in ABS, and the rest of the system in DES. The result agrees with Abdelghany, Eltawil e Abdou (2016), which stated that ABS models take a long time to build and require a lot of data, so DES/ABS models can use DES to represent the general system, and ABS only to represent the human behavior.

The time to process the simulation integrating the patient in ABS and the resources in DES was faster than the model only in ABS. However, it was slower than the DES model and the model with the patient in DES and the resources in ABS. This is because the patient modeled in ABS has more statecharts in his diagram. The cost of developing a hybrid model is also influenced by the hourly cost. It is also emphasized that, in this case, it needed to be a platform that allows integration of two methods in the same model. Knowledge needs to be specialized, mastering its implications as described by Jun et al. (2011). In hybrid methods, it is necessary to know the problem and the implications of just the patient's behavior or just the behavior of the resource within the Emergency Department. Good data is also needed, mainly on the behavior of the modeled agent. The other data can be only of the steps, quantity, and duration of the activities.

Based on the theoretical background, the construction of the conceptual model, computational model, and analysis of the results of each simulation method, an orientation framework was devised to use each simulation model, as shown in Figure 47. The problems were classified according to Salmon et al. (2018), in six categories. As can be seen in Section 3.6, the majority of simulation efforts seek to solve process problems, and the results for the emergency department, whether it be waiting times, length of stay, or service times.

The DES method is more usable when you want to model the flow of the emergency department process, identify bottlenecks, assess impacts of adding or removing technical resources, such as doctors and nurses, and assess the service capacity according to the patient entry flow. The managerial perspective can also be applied by including the remuneration of resources, or risks of creating a new service. The advantage of the DES method is its

Figure 47: Orientation framework



simplified fast modeling, which uses fewer data and requires less knowledge of the system to be modeled. However, it does not observe the side effects of the decisions taken, considers that the entire patient and resource is only passive to the flow designed, according to Siebers et al. (2010) and Abdelghany, Eltawil e Abdou (2016).

The ABS method can model the same problems as the DES method, but considers the behavior of agents as an important variable in the process, which is not easily modeled by DES. Thus, it agrees with Macal (2016), that ABS is not replaced by other methods with the same quality of information and scenarios. that ABS is not replaced by other methods with the same quality of information and scenarios. In ABS, the patient's and the resource's behavior is analyzed when the capacity of the technical resources is changed. For example, a hypothetical scenario can be modeled that, by reducing a doctor, the other doctors may feel overwhelmed and decrease their productivity. This can increase the patient's waiting time, increase the number of patients who leave without being seen by a doctor, or decrease the clinical quality of doctors, generating more referrals of patients for observation or increasing the return to the emergency room another day. In the ABS method, political and behavioral impacts are best demonstrated. However, for this, modeling and running this behavior in the system, takes more time to complete the process and needs more data, according to Siebers et al. (2010) and Abdelghany, Eltawil e Abdou (2016).

The hybrid method integrating DES and ABS has the potential to balance the need to investigate the behavior of a particular agent in a system modeled in DES that is built more quickly. Therefore, identifying the level of detail and abstraction, described by Djanatliev e German (2015), help to decide which method to use in each stage of the model.

Models that use DES and ABS hybrid simulation tend to analyze more managerial problems, such as Nouman, Anagnostou e Taylor (2013b), Hagtvedt et al. (2009), Fakhimi et al. (2014) and Aringhieri (2010) who modeled the behavior of ambulances in ABS according to the flow of care modeled in DES from emergency departments. However, they also assess process and performance problems, resources and capabilities. The proposal devised in this research demonstrates that it is possible to model the patient in ABS and the other resources of the system in DES. This analysis is applicable to investigation of the behavior of a patient when the capacity of the service is changed, or when a new protocol is implemented, or a new flow is developed. This method is of interest when the behavior and interaction of technical resources are not necessary, for instance when modeling resources as agents in ABS and patients in DES. In this view, resources change their behavior when a scenario changes, for example, when the amount of resources changes, or when a new routine doctor does not communicate with the doctor on duty. The impacts of these interactions can generate changes in the demand for patients referred for observation. Another example, is what the reaction of doctors and nurses is when changing the patients discharge flow. A similar study was conducted by Abdelghany, Eltawil e Abdou (2016) at a radiology center.

Most problems can be solved by any of the four methods, although it is necessary to assess which is the best approach to use. For this, it is necessary to question what is desired to be visualized in the problem and the simulation, what are the possible solutions desired, and, mainly, if the behavior and/or the interaction among the agents in real life interfere with the problem or solution desired.

The question of whether the agents' behavior and interaction interfere with the analysis is the first step in determining which method is most appropriate for the situation investigated. If detailed individual information is not required, the suggestion is to develop the study using the DES method in which the emergency department is simulated from the process flow. In this case, data collection focuses on simpler information, such as patient entry data, resource capacities and duration of activities.

If the behavior and interactions of the agents are necessary for the analysis of the problem, it is advisable to use the methods that model in ABS or hybrid. To define whether the simulation will be completely developed in ABS, it is important to assess whether the behavior and interaction among patients and technical resources influence the solution to the problem, or assess whether other complex systemic impact interactions are needed. For example, does the doctor's decision influence the patient's next statechart, which, in turn, influences the nurse's next statechart? If so, the suggestion is to simulate in ABS. In this situation, complete data collection is necessary, as the agents' statecharts, their movement, and the way they communicate among themselves are necessary. It is also necessary to observe the study environment assessing the individual behavior of each agent. Sometimes resource experience can be an important input.

As previously described, the requirement for details of the ABS method can slow development. If the interaction among patients and technical resources is not required to investigate the problem or propose a solution, it is suggested to evaluate what the necessary behavioral information is. If only the behavior of the patient is important, the hybrid method simulating the patient in ABS and the resources in DES is the most appropriate. On the other hand, when the behavior and interaction only among resources are important, the hybrid method simulating the flow of the patient in DES and the resources in ABS may be of more interest. In both hybrid methods, observing the study environment of the agent is important, in addition to the quantitative data and flow data for developing the model in DES.

Chapter 4 presented the design of the conceptual model, the development of the four simulation methods, and the comparison of the results of the four models, demonstrating that it is possible to simulate the emergency department with different simulation methods and obtain similar results. The decision of the most appropriate simulation model depends on what is to be investigated and solved, as each method has its advantages and limitations.

It can also be highlighted that involving the specialists of the researched institution in the study can help to build solutions for the simulated environment. In the case of this study, the author of this research also works as an analyst in improvement projects and processes within the institution. It was necessary for this person to learn about simulation methods and programming techniques. This practice slowed the development process, although it helped to project improvements in the emergency department, still in the construction phase of conceptual and computational models, as it was already possible to observe opportunities for improvement.

Simulation models contribute to the advancement of improvements in the emergency department. The decision of which simulation method to use depends on the resources available, but mainly on how one wants to evaluate the problem and the proposed solutions offered in the emergency department. Allowing health managers and researchers to choose the most appropriate simulation model for their emergency department. The conclusion of this chapter formalizes the achievement of the last specific objective of this research. In Chapter 5, the Final Remarks, the limitations and opportunities for future research will be presented.

5 FINAL REMARKS

This research assessed the models of simulation of discrete events, agent-based and hybrid in the patient flow of an emergency department. A theoretical background sought to identify the environment of an emergency department, the DES, ABS and hybrid methods using the combination of DES and ABS in the same model, the main modeled agents, application categories, inputs and outputs necessary for the development and assessment of simulation models. The patient flow in emergency departments was identified and this indicated the need to characterize which problems, inputs and outputs are expected for each simulation method (JUN et al., 2011).

Then, based on the literature, the conceptual model was developed and data were collected at the hospital in the study environment. There was also definition of the main criteria necessary to develop and assess the patient flow and the simulation models used.

With the conceptual model validated by the hospital administrator, and with the data collected, the latter were analyzed statistically and prepared to be used as inputs in the simulation models. Computational models of the emergency department under study were developed for four simulation methods: discrete event simulation (DES), agent-based simulation (ABS), hybrid simulation integrating the patient in ABS and the resources in DES, and another integrating patients in DES and ABS resources.

After the simulation data had been validated with the real data, 15 replications of each simulation method were run, and their results compared among the models to assess the level of adherence. When analyzing the theoretical background with the experience of developing each of the computational models and comparing their results, it was possible to assess the models of each method considering the criteria developed by Naseer, Eldabi e Young (2010) and Jun et al. (2011), namely the time, cost, knowledge and necessary data, and also develop an orientation framework for when to use each method. This framework helps managers and researchers to choose the most appropriate simulation model to apply in their emergency department, considering the advantages and disadvantages of each method.

The DES method is best suited to assess processes and results based on the emergency department's service flow, considering the demand and capacity of the resources, although it does not consider the behavioral effects of the simulated entities, considering all liabilities to the model designed according Siebers et al. (2010). The ABS method, on the other hand, adds value to the quality of the data on the behavior and interactions generated in the environment, considering each statechart of the modeled agent as an important point in the emergency department process. However, the model only in ABS, according to Denton (2013) can become very complex, with slow development and an excessive need for data.

The hybrid method combining DES and ABS can be modeled from two points of view, that is, considering the patient in ABS and the rest of the system in DES, or, on the contrary, considering the patient flow in DES and the human resources in ABS. This method is an alternative when it is necessary to investigate the behavior of the agents of only one piece of the complex emergency department system. It is a faster more objective alternative than ABS, although it is necessary to study the forms of communication between the two methods, as suggested by Brailsford et al. (2018).

The assessment of the different simulation models contributes to advancing the resolution of the real problems of the emergency department. The decision on the most appropriate simulation approach will depend on what one wants to investigate and solve. As stated in Djanatliev e German (2015), it is important to assess the level of abstraction desired, considering or not the interaction among the agents and the availability of resources, such as data and knowledge about the implications of the environment. This research helps evolution in the development of modeling and simulation in real environments, and, currently, the application of simulation by health managers and real problems is still low compared to other sectors, as stated in Naseer, Eldabi e Young (2010).

The involvement of the researcher who is also a manager in a health institution contributed to the institutionalization of simulation methods as an applicable tool in the real health environment. Thus, it is suggested that the entire simulation experiment involves field professionals to support or even run the simulation models. These simulation models also contribute to solving other problems in the health environment, changing the methods according to the needs of each problem

5.1 Research limitations

The limitations were primarily due to the choice of simulation methods, which considered only computer simulation and excluded the system-dynamic method, because it considers a method that assesses at a more abstract level, as in Djanatliev e German (2015), Thus, methods that simulated the operation of the emergency department were sought.

Data collection also demonstrated limitations, such as lack of detailed data on requesting and executing exams, as well as the activities of the observation unit. In addition to inconsistent data in some stages of the process, it is necessary to analyze the data. The research was also limited to only one study unit, which was the hospital at which the researcher worked. The researcher's bias when working on the case studied can also be considered a limitation of the research.

The researcher’s knowledge about how to develop simulation models in Anylogic software and how to program in Java was also a limitation, making the research process slower and requiring specialized courses taught by representatives of Anylogic itself.

Another limitation occurred when using the software, Anylogic 8 Personal Learning Edition, version 8.4.0, which has a limited number of 10 agents per model, and it is not possible to model the radiology center stage, only considering its time in the model.

5.2 Recommendations for future work

Throughout this research, other study opportunities have been listed, such as using the System Dynamics method in hybrid methods supporting the patient feedback loopings, and the application of strategic health policies and their impact on the operation of the emergency department. The computational models were developed according to the reality of the study environment, although it is suggested to experiment with different scenarios seeking the optimization of results and resources.

Another possibility for future study is to integrate Lean Healthcare and Health 4.0 as enhancers for improvements in the simulated models. Using a map of value flows and technologies in the simulated environment for later application in the real environment. Finally, one of the main problems in the emergency department is the high volume of non-urgent patients visiting the unit. With the hybrid modeling in ABS and DES, it is suggested to model the impact of the creation of a Primary Health Care unit close to the emergency department to share patient care.

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