Adaptive Agent-Based Model and Simulation Metasystem for Emergency Departments

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Abstract. Hospital Emergency Departments (EDs) are one of the more complex units of the healthcare system, that require coordination of both medical personnel and other resources to manage situations effectively. This article establishes the basic principles to design primitives of an Agent Based Modeling and Simulation (ABMS) modular system, that allows the creation of computational models that, used as Decision Support Systems (DSS), allows the EDs to achieve the highest possible level of quality of service, given the resources available.
Inspired in the modularity of Lego® blocks, this ABMS system has attempted to shift from a monolithic approach to an adjustable system. This means that the system allows the description of the metasystem and agent box used to build the computational models (simulator) that can be employed as DSS.

Keywords: Emergency Department, Agent-Oriented Modeling, Emergency Healthcare Systems, Modular Design, Decision Support Systems

1 Introduction

The emergency care received in the Emergency Departments (EDs) is affected by a variety of factors. Both, fast response rates and foreseeing what may happens in the future are essential. Simulation is a useful tool for dealing with this challenge [1] helping to investigate alternative scenarios and answering "what if" questions to show how different ED management problems can be solved [2]. This increases anticipation against danger situations thereby improving the EDs ability to handle increased demand particularly during exigent times such as flu outbreaks or pandemics which have recently stretched their capacities [3].

Simulation models have been used to assess how an increasing arrival of patients into the ED affects waiting times and general provision of services. Consequently, this information can be used to develop targeted interventions to reduce overcrowding while maintaining quality standards of care. In addition, by studying these hypothetical cases, healthcare administrators can implement measures that speed up operations and timely patient flow even when there is an increasing demand.

Simulation becomes an important tool for analyzing complex systems like EDs. There are two simulation techniques that stand out because they work well in practice: Discrete Event Simulation (DES) and Agent-Based Modeling and Simulation (ABMS). DES allows for discrete event analysis over time and models how every single incident affects the flow and function of ED. This technique helps to understand sequences and, on the other hand, does not consider all human interactions. In contrast, ABMS is rather more comprehensive in approach. It models the behavior and interactions of many individual agents such as patients, nurses, environment. Studies suggest that, with these characteristics, ABMS would be better suited to simulate complex systems like ED [4][5]·

Different research groups have developed ED simulations based on the accumulated knowledge of experts but taking a unitary design, what means that software ends up being built into one large package with all its parts tightly integrated into the program. The protocols developed often cannot be easily adapted for use elsewhere. To solve this problem, researchers have two main options: adapting existing programs, a challenging task, or creating a new, more flexible program from scratch, a major undertaking.

Drawing inspiration from the adaptability of modular building systems like LEGO® blocks, a novel approach emerges for ED simulation: deconstructing monolithic models into a flexible "agent repository". This concept provides a comprehensive collection of virtual entities representing all potential ED components, configured in a standardized way with primitives for basic interactions. It offers an easy method to incorporate healthcare professionals, patients, and equipment, along with a standard procedure to add more agents into the system.

The remainder of this article is structured as follows: Section 2 provides a concise summary of the literature review; Section 3 presents the fundamental properties of the proposed Metasystem; Section 4 summarize the analysis of the primitive elements of the Metasystem; finally in Section 5 future work is outlined.

2 Related Work

This section presents various works related to ED simulation, firts the actual situation in different contexts and after the contributions of the HPC4EAS research group in this field.

2.1 Literature Review

The adaptability of simulation models to various health systems seeks to improve EDs. This flexibility will allow the implementation of the proposed modular metasystem, which can be adjusted to the specifics of different emergency care environments. There are various research groups that have been working on ED modeling and simulation, which are good reference models. For instance, the 3S Research Group has developed an interactive simulation-based decision support framework for an ED in one of the largest University Hospitals in Dublin [6].

It is important to look at healthcare systems in different social and economic contexts. Some of the differences include medical service accessibility and funding mechanisms among nations which result into the structure and operation of ED. Following the studies of the World Health Organization, ED setups can be classified in four main types. Each type has its own way of being run, who it covers, and how its paid for [7]. A comparison of healthcare models is summarized in Table 1.

Table 1. Comparison of Healthcare Models

Model	Funding	Control and Management	Coverage and Features
Beveridge	Income taxes	Government	Universal, public
Bismarck	Social insurance	State regulates	Employment-dependent, copayments
National Insurance	Taxes and insurances	Mixed	Universal, greater choice of providers
Out-of-Pocket	Private	Individual	Limited access, no financial protection

Each model reflects a different philosophy regarding the role of government, individual responsibility, and the principles of social solidarity. While the Beveridge and National Health Insurance models focus on universal coverage guaranteed by the state, the Bismarck and Out-of-Pocket models present a more segmented or individualized approach to healthcare coverage, which causes different types of ED operations in each case. The Beveridge model is implemented in countries like Spain, Portugal, and Finland, the Bismarck model in countries like Austria, Germany, and Switzerland, and the National Health Insurance Model is found in Japan, Canada, and South Korea [8].

There are tools like VisualizER, a DES tool that demonstrates how simulation can be used to optimize EDs [9]. Although it allows simulation of emergency operations, it does not offer the capability to model the individual behavior of agents, which is a crucial component for predicting unexpected events.

2.2 HPC4EAS Research Group Contributions

This section includes a summary of the results obtained by High Performance Computing For Efficient Applications and Simulation research group (HPC4EAS) of the Universitat Autònoma de Barcelona (UAB). The group have carried out several projects in cooperation with the ED staff of the Sabadell Hospital (Corporació Sanitària Parc Taulí), a healthcare institution that serves a reference population of over 400,000 people, handling in ED an average of over 150,000 patients per year, playing a crucial role in the healthcare system of Catalonia and, by extension, Spain [10][11].

The research group has designed an ED conceptual and computational model using the ABMS techniques, that includes two kinds of agents: active and passive. Active agents represent people, who act upon their own initiative (patients; admission staff; sanitarian technicians; triage and emergency nurses; and doctors) and passive agents represent systems that are solely reactive (loudspeaker system; patient information system; central diagnostic services; etc). The model includes both the environment and a communication model, because the ED is divided into different zones in which different types of agents may act, maintaining interactions that also may be different, and such interactions are carried out through communication.

The behavior of active agents has been modeled using Moore State Machines. The Agent will remain in a specific state until, through the interaction with other agents, he/she receives an Input (an Output generated by other agent), that causes a change in the state of such agent, generating an Output that sends to the agent with who he is interacting. The agent's state machine will move to the next state (S_{t+1}) following the transition, which may be another state or the same one in which agent was before the transition. Transitions between states depend on the current State at time t (S_t) and the Input at time t (I_t) [12].

To reproduce the system behavior the model organizes patients according to this severity classification, what is identified in the triage process, assigning patients with levels I to III to zone A for priority care, while those with less severity, levels IV and V, are placed in zone B, designed for less urgent situations. This segmentation is important for managing patient flow [13].

Once the conceptual model had been set up the group developed the computational model (simulator) with NetLogo software [14], a modeling environment designed for ABMS. The simulator has been adapted and applied to analyze how to optimally use the limited resources available in the ED [15], to generate information about specific scenarios that, while possible, rarely occur in reality [16], and thus learn about the best way to manage them, or also to analyze, model, and simulate the transmission of the Methicillin-resistant Staphylococcus Aureus (MRSA) virus [17], and its effects on the operation of the ED, in order to explore the potential benefits of adopting preventive measures.

3 General Characteristics of the Metasystem

In order to build on previous work and progress made in the field of modeling and simulation of EDs using ABMS techniques, we propose a metasystem. The aim of this system is to manage modularity of ABMS used for developing adaptable simulation environments.

The metasystem will therefore arise from a conceptual model that ED experts have developed collaboratively together with the disaggregation of existing simulators hence helping define standard components applicable in different health environments. This would then allow for an efficient transition from a given conceptual design to a computational configuration within the metasystem whenever a computational model for any ED has to be generated. With

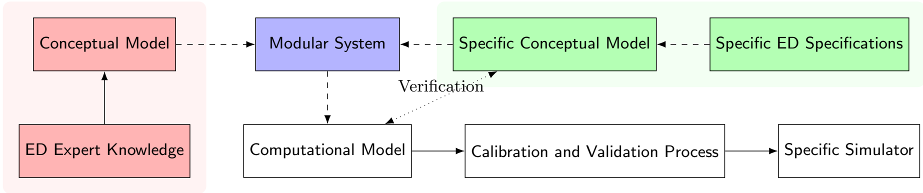

Fig. 1. Diagram of the design process of a simulator using a modular system for a specific ED.

the computational model ready, it will be necessary to go through calibration and validation processes before ending up with specific simulator. This process is shown in Figure 1. The section that is discussed in depth here is shown on the left of the diagram, while the areas of a ED that are intended to be modeled using the metasystem are represented in green.

The objective is to develop a platform that aids in constructing computational models of EDs, that have an intuitive interface based on blocks. These blocks symbolize various agents and functions of ED and can be altered to suit individual needs. This means that flexibility should be one of the crucial aspects; hence the system should allow for combining blocks in different ways depending on specific operational characteristics of diverse EDs. For instance, it allows exploring how changes in staff roles might affect such things as: if a nurse assumes more or less responsibility than they currently have or if anyone else would take over their duties. Such transformations are expensive in traditional systems. This requires analyzing state variables that will characterize different agents within these systems for their disaggregation, as well as determining how their transition from one state to another will occur.

In this context, three major groups are identified, two for active agents and one for passive agent, to study variation in their operation strategies between them. Among the active agents, can be find common elements that all of them share, such as the internal identifier in the system, the actual location corresponds to the agent's current position and the action currently being taken by the agent.

For patients as a particular case, there are complex state variables and transitions. Three particular variables used in this modeling are personal details, priority level and communication level. Patients are often recognized as among the most important agents in an ED. They gather data on their **personal details** such as age and gender that is considered for customized treatments. The appointment of a triage-based **priority level** indicates how urgently medical care should be delivered while the level of **communication** between a patient and ED staff shows how successful these interactions are done.

The diagram displayed in Figure 2 shows a patient's journey through an ED right from their arrival. This is when they come, get unique identification number assigned, and the time they arrive are documented. In case medicalized ambulances bring them, then triage has already been done on the spot; other

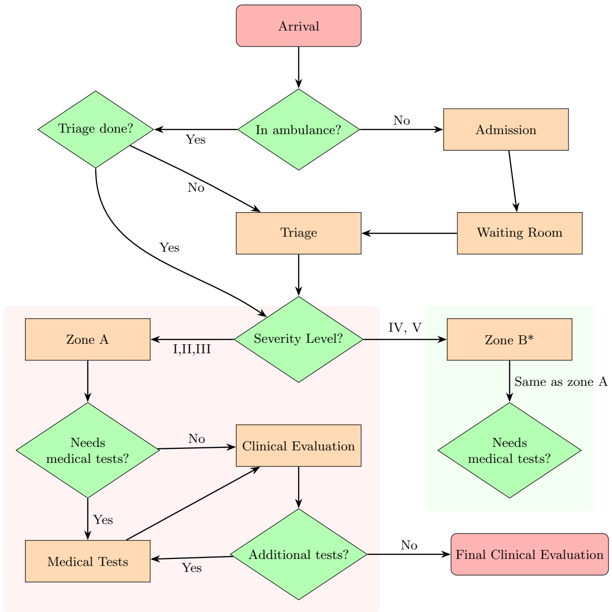

Fig. 2. Diagram of the process patients go through in the ED.

than that, the process starts with them being admitted either singly or aboard nonmedicalized ambulances.

Triage is where patients' priority levels are defined to guide them through the system to either to treatment areas, a separated zone (Zone B in the figure) with one specific waiting room and attention boxes for less severe cases (patients with priority level IV or V) or directly to a carebox (Zone A) for patients with more critical conditions (patients with priority level I, II or III).

Communication level counts most at every stage starting from whether it is necessary to carry out any medical tests until there is need of making decisions about further treatments. Evaluation cycle of treatment followed by possible re-evaluation continues until resolution point is reached: patient is discharged or further actions are taken according to their needs.

Every phase of this procedure represents how the patient's state variables interact with the ED system's actions. The objective is to develop a system that includes an "agent box" to select the necessary agents for this system and adapt it based on the ED requirements, as shown in Figure 3.

As research on active agents in the ED continues, doctors are among the principal ones, and their state variables symbolize their place in the care giving. Unlike patients, there are direct things that define a doctor's action; such things include tasks that have been assigned to them and a series of sequential medical procedures. Doctors' actions can range from not responding, which could mean waiting for the next patient, to more interactive acts such as calling a patient, asking multiple questions to obtain more information, making an initial diagno-

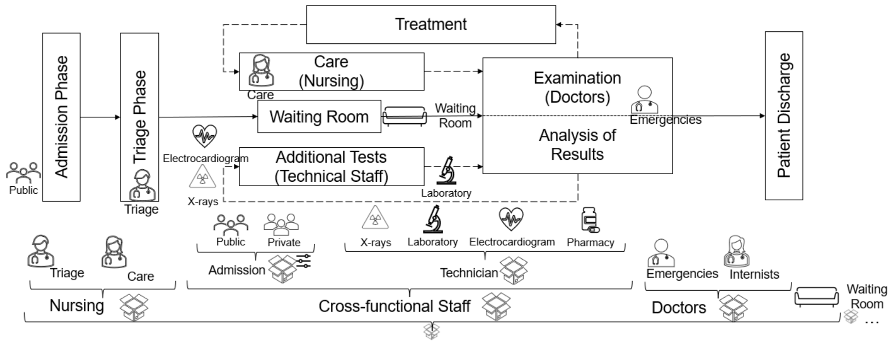

Fig. 3. Example of Modules Utilized in an ED.

sis, and prescribing specific tests or treatments. A doctor may also be actively waiting for the results of laboratory tests he or she has ordered and then decides what to do next with this result, including discharging a patient from the ED or making final diagnoses that will be entered into the computer system.

In the ED, a doctor's level of experience, which can be low, medium or high, influences his or her performance and is therefore an important aspect that determines work in the ED. A doctor with a lot of experience will make quick diagnoses or handle difficult cases in a short time. To do this, the metasystem has incorporated a state variable to solve these problems.

Efficient care depends on how well the Information System (IS) functions in an ED. It orchestrates decisions arising from requests made. Firstly, the IS checks the pending tasks and therefore moves forward to obtain reports, register patients and issue medical alerts based on this aspect. Decisions about whether patient data already exists have implications for later steps, such as recording new information or adding it to the existing system. The workflow helps process information and update medical records at all times.

To change state, IS depends on interactions with active agents operating in their environment. The operationality of the ED may be affected by this categorization into low, medium and high levels. As a passive agent within the ED, the IS plays an important role in coordinating the different parts of the health system. Your ability to process information accurately is necessary for smooth workflow and to ensure patients receive timely care. It is a component that supports all ED operations, from admission to patient discharge.

4 Analysis of Primitive Elements of the Metasystem

The system needs a series of primitives that require exhaustive analysis to operate under certain standards. We always aim to maximize respect for the agents' behavior. For this, we must have a standard communication system through which all agents can communicate, personalized for each one depending on the message and content.

To analyze the primitives, it is necessary to examine specific cases. First of all, let's imagine an emergency waiting room, where we have a number of people sitting and others stand up. What elements do we need in an ABMS system and how would they function to resemble reality as closely as possible?

Considering it is impossible to analyze all the alternatives a complex agent like a human could take, we need to narrow down the most common cases within the ED. If we enter a room and it is full or if the environment is tense, our agent might move to the reception. The goal is not to resolve these types of scenarios and provide maximum specificity at this point, but to obtain that data through the agent optical system and have a perception of the space, so that the main elements affecting the service can be analyzed depending on each case.

If a person enters in the ED waiting room, they will indicate to a room agent that they have entered, thus changing their location simultaneously. When the agent enters a room, he has no information; he has to analyze it. That is why the environment acts as an agent storing that the person who entered is in that room. Additionally, it will transmit its current state so that the agent can register it internally, but it is important to realize the natural limitations we have. When we enter a room, we do not really store all the information; we analyze the information we need at each moment, observing the room again when we are going to make a decision. Each time there is an entry or exit from the room by an agent, we may see or hear it, or not, depending on our observation capacity. This will be a state variable of the observing agent, which always receives the visual room's information. In this scenario, the room will consider its state to inform about the room's characteristics at the precise moment patients enter.

Moreover, the room's functionality is not limited to this. It may have other state variables such as passive elements like seats, how contaminated the environment is due to a virus, among other possibilities that it will provide whenever we are in it, even though some may not be perceptible.Therefore, the rooms need state variables that contain the list of agents and the list of resources available in the room. Any interaction in the room will be carried out through communication primitives. Communication primitives are a series of predefined states in the different agents that may or may not have the capacity to communicate. This data set will contain an identifier of the message sender, to identify it if necessary, a destination, who the message is directed to (It can be addressed to a room, a specific person, or a nearby area). Each communication will contain a message indicating the purpose of the communication, such as a request for information, an alert, and content with the message to be transmitted.

5 Conclusion and Future Work

Simulation in EDs is greatly beneficial in addressing the increasing complexity and saturation these services currently experience. The ability to analyze problem situations in advance through the simulation of scenarios allows EDs to respond effectively to adverse situations, especially in critical contexts such as pandemics or disease outbreaks. Simulation not only improves response capacity to growing demand but also contributes to the strategic planning of EDs.

Developing simulators in ABMS marks a significant milestone where models can be adjusted depending on the different characteristics of various EDs. The transition from monolithic models into a modular system called "agent box" allows them being modified for any design/ED configuration; hence it becomes flexible enough whenever changes need to happen. It is more effective because it can reflect any healthcare system with its unique operational features, allowing rapid customization and re-configuration.

This simulation proposal differs from other solutions, such as DES and tools like VisualizER, in its focus on agent adaptation and modeling. Through the use of ABMS, it is possible to model individual behavior between agents. This provides an adaptable system for healthcare professionals, enabling more effective management of EDs. Nonetheless, there are limitations as well as potential directions for future growth of this technology. The first one is the number of predefined modules in the "agent box" that could be solved by creating a common repository where new needs could adapt old modules. Additionally, expanding the use of modular systems in EDs to other healthcare and geographic contexts would offer insights that may improve ED efficiencies globally.

The proposal of an ABMS-based metasystem for ED simulations contributes to improving knowledge about and managing these services. By being able to model intricate human interactions, this innovation opens up new avenues through which EDs can be readied for contemporary or future challenges. Modularization approach toward system evolution coupled with module development collaboration will contribute significantly in enhancing the capabilities of simulations thereby giving continued.

In the future, a comprehensive review will be essential to expand the number of building blocks that use the primitives to develop an inclusive conceptual model and metamodel. This analysis will require interdisciplinary cooperation between clinical knowledge and ABMS.

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