Statistical and Requirement Analysis for an IDM Tool for Emergency Department Simulation

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Abstract: Emergency Departments (ED) are spaces prone to congestion due to the high number of patients. This problem, known as overcrowding, has negative effect on patient waiting time. In order to find a solution, analysis of the flow of patients through Discrete Event Simulation (DES) is a relevant approach that models the operation of a system through a sequence of events. This technique relies on high-quality input data which needs to be previously managed in a complete process known as Input Data Management (IDM). The objective of this research is to present our progress in the development of a software application to efficiently automate the IDM process required for DES of ED. Preliminary findings and results presented in this paper include the problem definition, the evaluation of required statistical methods, and the gathering of specific requirements from a case study with real data. Based on these results, this paper describes the initial architecture of a software application that satisfies the identified requirements.

1 INTRODUCTION

One of the main problems in Emergency Departments (ED) is over-crowding, which is according to Duguay and Chetouane (2007), "the situation in which ED function is impeded primarily because of the excessive number of patients waiting to be seen, undergoing assessment and treatment, or waiting for departure comparing to the physical or staffing capacity of the ED". Overcrowding is thus recognized as a global problem, which has reached crisis proportions in some countries. It has direct implications in the well-being of patients and staff, mainly due to waiting times derived from process deficiencies, the inappropriate placement of physical and human resources, and budget restrictions. In addition, it can affect institution's financial performance and reputation (Komashie & Mousavi, 2005).

One of the strategies to mitigate the adverse effects of overcrowding is using Discrete Event Simulation (DES) to provide analytical methods to assess and redesign processes, and support data-driven decision-making. DES modeling has become an efficient strategy for solving real-world problems, it provides a conceptual framework that describes evolving stochastic dynamic systems used to test hypotheses and forecast expected behavior. There is a broad range of applications of DES in Healthcare, Manufacturing, System Operations, Logistics, and more (Rodriguez, 2015a). DES models, in ED context, aim to reproduce the flow of patients and their relationship with the different areas, personal, and resources available to solve specific problems.

The success of DES applications depends on the prior preparation of high-quality input data. Some of the event data required in DES are represented in probability distributions. The parameters describing the underlying distributions are a key input for the simulation. The process that involves transforming raw data into a quality-assured representation of all parameters appropriate for simulation is known as Input Data Management (IDM) (Skoogh et al., 2008).

Input data preparation is one of the most crucial and time-consuming tasks in a DES project (Robertson & Perera, 2002). According to (Skoogh et al., 2012) the input data management process consumes about 10-40% of the total time of a DES project. In most cases, practitioners transform manually raw data from different sources into appropriate simulation input (Robertson & Perera, 2002) and separately from the software used for the

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simulation. The automation of the data preparation phase has the potential to increase efficiency in DES projects, by integrating data resources (Skoogh et al., 2012).

While reviewing the literature, we did not find any commercial tool for IDM automation and identified only three open-source tools allowing such procedure, namely, GMD-Tool (Skoogh et al., 2010), DESI (Rodriguez, 2015b), and KE Tool (Barlas & Heavey, 2016). Some of the main lacks we found when reviewing them include the fact that these tools do not offer features for sharing data and results, limiting the opportunities for collaboration by allowing other researchers to replicate the process to obtain similar outputs. Moreover, the reviewed tools do not have features for managing projects and generating data quality reports. Although these have features for fitting some statistical distributions, they do not fit all the possibilities that can be used for ED operation simulation, such as, Markov chains modeling and do not have features for evaluating distribution properties. In addition, in the research works presenting them there are no information related to their utility for handling large datasets or running in tensive workloads and only examples with small volumes of data on personal computers are presented.

To identify potential current challenges in the data preprocessing tasks in the case of a DES project studying ED crowding, a case study analyzing a sample of the patient flow data of the ED at the Hautepierre Hospital located in the city of Strasbourg, France, was carried out. The case study has two main objectives: first, to identify the statistical methods to generate the required inputs in a simulation of the patient pathway within an ED. Second, to determine the preparation and validation requirements to guarantee data quality. As a result, the case study reveals limitations regarding the automation of the required processing.

In this context, the research problem addressed by our research is: how to automate the IDM process for DES models to address the overcrowding problem in ED? To deal with this question, this article presents our progress towards an open-source cloud-based web application for IDM.

The article is organized as follows: section 2 presents related work in the domain. Section 3 presents the IDM requirements and evaluation of required statistical methods from the analysis of the case study. Section 4 introduces the IDM solution's architecture. Finally, section 5 presents conclusions and recommendations for future work.

2 RELATED WORK

2.1 Simulation of ED Operation

Patient flow in an ED can be analyzed through both analytical and simulation methods. Analytical methods are often insufficient at dealing with complex systems such as emergency rooms, while simulation models are more appropriate to capture and optimize the performance of these (Ghanes et al., 2014).

The most common methods for simulating ED operations include dynamic systems (Robertson & Perera, 2002), experimental design (Kuo et al., 2012), survival analysis (Levin & Garifullin, 2015), stochastic process (Ghafouri et al., 2019), linear programming (Furian et al., 2018; Ghanes et al., 2014). Such approaches cover a wide range of applications that can fit in the following categories: resource allocation, process-related optimization, and environment-related analysis. The usual procedures for conducting a simulation study may vary according to the nature of the study. However, there are typical stages: problem formulation, setting study objectives, developing a conceptual model, data collection, model building, model validation, and verifications (Al-Aomar et., 2015). Our approach can be considered as the automation of processing tasks after data collection and before building the simulation model.

Regarding the construction of the conceptual model to analyze overcrowding problems, it is necessary to know in advance the configuration of each ED, which depends on the needs, staff, capacities, and areas of the health institution. The possible areas described in studies such as (Ghanes et al., 2014; Komashie & Mousavi, 2005; Kuo et al., 2012; Levin & Garifullin, 2015, Mohammad et al., 2019; Armel et al., 2003) include waiting room for walk-in patient arrival, the registration and sorting zone, shock room or resuscitation room, assessment areas (physician, paediatricians), examination rooms (X-rays, CT SCAN, echocardiography, blood- test), among others. The staff usually refers to physicians, nurses, doctors, specialists, residents, practitioners, medical students, consultants, registrars, engineers, and administrative staff.

The data source plays an essential role in obtaining data on the main studied operation variables, i.e., arrival patterns, time spent on different activities by care providers, inter-arrival times and length of stay (LOS) distributions (Ghanes et al., 2014; Vanbrabant et al., 2019). Data obtained about inter-arrival times and service times, volume and mix of patients staffing levels, types and duration of treatment are used to determine model inputs and outputs. Once the data is collected, it is exploited to calculate processing times, statistical distributions, routing probabilities, among others.

The validity and credibility of the data models are evaluated using different approaches, the first of which is the evaluation by experts and senior management, secondly the sensitivity analysis, thirdly the emulation of the models, and finally, by considering the source of external variability. In most cases, historic consistent data of the process such as triage category, arrival date and time, and time-stamp records of the triage start time, consultation start time, and departure time of each patient are used to test hypotheses and to evaluate scenarios about staffing levels and schedules (Ghanes et al., 2014).

2.2 IDM

Skoogh and Johanson (2008), defined Input Data Management (IDM) as "the entire process of preparing quality assured, and simulation adapted, representations of all relevant input data parameters for simulation models. This includes identifying relevant input parameters, collecting all information required to represent the parameters as appropriate simulation input, converting raw data to a quality assured representation, and documenting data for future reference and re-use". Data collection has multiple inherent difficulties (Bokrantz et al., 2018). Organizations can have multiple data sources and systems to collect the data from. Second, accuracy, reliability, and validity are the analyst's responsibility when extracting and preparing the data for the simulation; those procedures, in most cases, are made manually, which makes it prone to errors. In a survey presented in (Robertson & Perera, 2001), it was inquired about the most frequent issues in simulation projects, considering data collection issues: 60% of respondents indicated they manually input the data to the model; 40% reported they use connectors to an external system like spreadsheets, text files or databases. In summary, as described in (Furian et al., 2018), the main challenges in this process are, in the first place, manual data collection and data entry, which increases the likelihood of data entry errors arising from human manipulation of data. The inherent difficulties of the manual process compromise the quality and integrity of the data. In addition, multiple manual files handling to maintain and process data makes it difficult to track errors and reproduce procedures.

3 STATISTICAL TOOLS AND REQUERIMENTS

This section focuses on analyzing the IDM tasks enabling to prepare statistical representations of the patient flow data of the ED of the Hautepierre Hospital in Strasbourg (France). In addition, we evaluate IDM tools that could be used for the analysis.

3.1 Emergency Department Description

We figure out the main steps of the patient flow by several, complementary means (see Figure 1). First, we observe the ED functioning during half a day. Second, we organize several workshops with three doctors of the ED (one senior doctor in charge of the ED and two junior doctors) in order to model the flow in the form of a BPMN private process model. During these two-hour workshops, we iteratively model and validate the patient flow with them. In this diagram, the patient flow is represented linearly as patients perform each of the activities consecutively. However, it is worth mentioning that there are iterations between the stages, as patients may require a procedure to be repeated or an exam to be performed multiple times. In addition, patients may undergo many different paths and do not necessarily goes through all the steps of the process. The number and types of diagnosis tests (Blood analysis, RX or CT scan) depend on the consultation and are not known as the outset, that is why we model the pathway using routing probabilities.

The data used in the case study were provided in comma-separated values (CSV) files extracted from the ED databases. The files contained anonymized records of patients and the events during their stay in the ED. The collected data contains records from June 22nd, 2020, to June 28th, 2020, of the ED flow of 795 patients. The records include information on the following events of the patient flow: arrival, triage, blood analysis (BA) (Coagulation, Hematology, Biochemistry), Computer tomography (CT) Scan, and X-rays (RX). The average throughput time is 5,52 patients/h. The ED uses a severity index for the assignment of degrees of emergency to decide the priority and the order of procedures. According to each severity level, the patients are assigned to one of three zones in the ED.

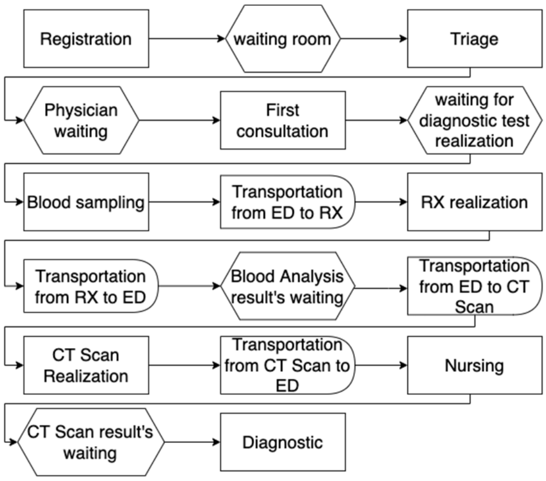

Figure 1: ED general process flow.

The data processing tasks were carried out by following the next activities: consolidating data sources, normalizing tables in which patients are in the rows as many times as events in the ED, verifying column names, verifying variable types, validating activity date formats, creating new variables from existing ones such as the duration of each stage of the process, generating flags for patients.

3.2 Statistical Analysis

3.2.1 Analysis Description

Different types of metrics are required to simulate an ED, which can be grouped into three categories: Arrival Patterns, Routing Probabilities, and Processing Times (Ghanes et al., 2014). In the following sections we carry out the necessary transformations with the data collected and identify the statistical methods to calculate them.

Arrival Patterns. The arrival patterns refer to the measurements made to the patients at the time of entering the emergency room. The metric used in this case is the arrival rate per hour/day.

For the modeling we consider $N(t)$ the number of patients arriving at the emergency room at a particular time t. It is assumed that patients arrive randomly and independently. In that case, it is possible to model the patient count as a Poisson process of parameter λ. However, when considering the temporal dependence of the counts, it can be considered as a Non-Homogeneous Poisson process with rate $\lambda(t)$. For the estimation it is assumed that the rate is piecewise constant on a set of time independent intervals. Given that $N(t)$ is a Poisson process with rate $\lambda(t)$ the distribution of the interarrival time follows an exponential distribution of parameter $\lambda(t)$.

Routing Probabilities. For the estimation of routing probabilities, we consider the sequence of events observed in the data as a Markov Process in which each state represents one event in the process, such as triage, or blood test, among others. The transition probabilities associated with the Markov Chain are in consequence, the routing probabilities. For the verification of this model, the following hypothesis tests on the properties of the chain are considered: Markov property, order, and stationarity of the transition probabilities, and sample size (Anderson & Goodman, 1957).

Processing Times. In the case, three elements can be distinguished in the processing times. The waiting times from the prescription of the exams to the moment they are performed, the time it takes to complete the exam and the additional waiting time to get the results.

Once the data were adequately arranged, we iterate over a set of continuous distributions to identify the one with the best fit for each variable. To test the goodness of fit, we used the Kolmogorov-Smirnoff test in which the null hypothesis evaluates that the data follow some specific distribution.

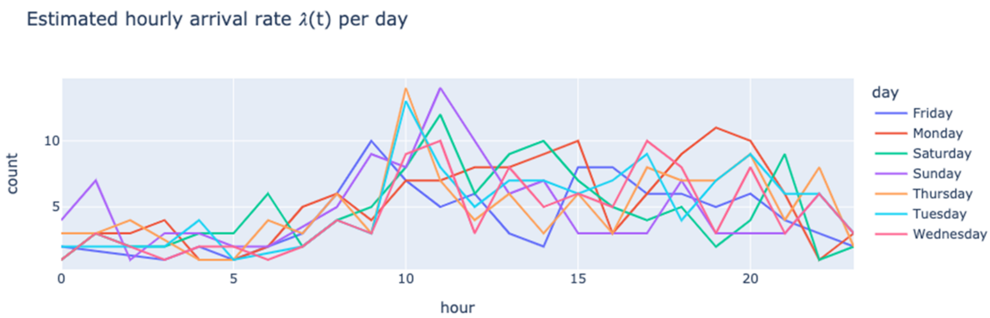

Figure 2: Estimate hourly arrival rate.

3.2.2 Analysis Results

Arrival Patterns. Firstly, the non-homogeneous Poisson process was estimated and the parameter λ was determined for all the one-hour intervals. Figure 2 shows the behavior of the parameter for all the days of the week, which can be evidenced by the bands of greater congestion and the peaks of patient arrivals during the day. The x-axis indicates the hours of the day, and the y-axis is the number of patients.

The curves represent the behavior of the intensity parameter for each day of the week. From these arrival patterns it is possible to construct the distribution of arrivals and inter-arrivals per hour, following the deduction mentioned above.

Routing Probabilities. The chain states are represented as the nodes of the Figure 3, which describes the transition matrix that indicates the probability of moving from one state to another. We can see that after triage, for example, the probability that a patient undergoes a blood test is 0.48, while not going through any stage is 0.44. Patients do not usually go directly from Triage to RX or MRI CT Scan; generally, to obtain these tests, a blood test is performed beforehand, where 70% are referred to one of these two tests.

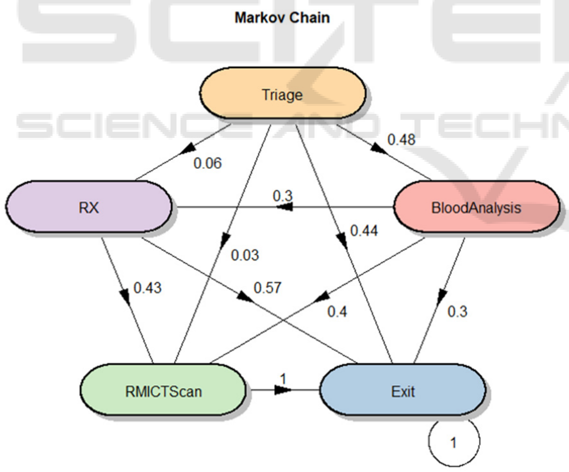

Figure 3: General routing probabilities.

Processing Time. After triage, the subsequent most frequent examination is a blood test. The collected samples are used for three evaluations, Biochemistry, Hematology, and Coagulation. For the Biochemistry blood analysis, we consider the distinction by severity index, and plot the histogram and the fitted distributions as seen in Figure 4.

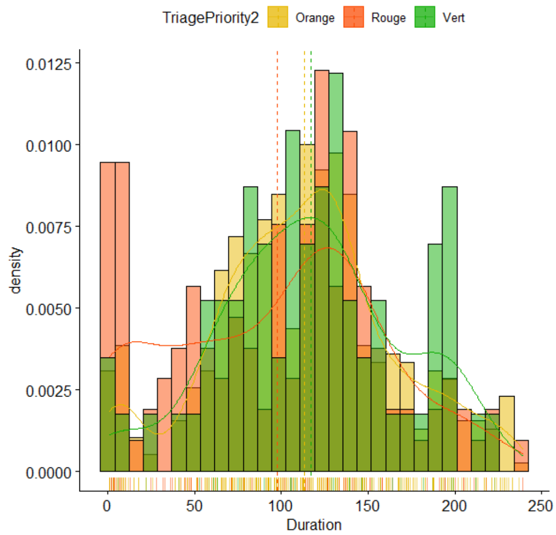

Figure 4: Biochemistry BT duration.

3.3 Requirements

From the manual process and interviews with the medical staff beforementioned as well as from interviews with two researchers in DES, we gathered the following requirements in terms of user stories:

- *User Accounts*: As a user, I want to register, login, change and recover my password into the app.
- *Manage Projects*: As an admin user, I want to create, edit, search, and delete projects into the app so I can manage resources
- *Invite User*: As an admin user, I want to invite users into the app so I can see grant access to projects
- *Manage Input Data*: As a user, I want to manage my datasets so I can analyse it on the platform. Acceptance criteria: Upload resource, encrypt and version files.
- Check Data Quality: As a user, I want to check the quality of my dataset so I can make sure my dataset is appropriate for simulation. Acceptance criteria: Perform data quality checks, generate Data quality reports.
- Process Data: As a practitioner user, I want to process my input data and obtain statistical representations of my variables in a compatible format for simulation software. Acceptance criteria: Display variables, fit distribution, display results, export results.
- Software Architecture: As a user, I want to process my data from a website to access my data and results anytime from the internet. Acceptance criteria: software and cloud architecture.

- Reproducibility: As a user, I want to replicate the analysis and results of my projects so I can make research is reproducible. Acceptance criteria: Public repository, cloud available, share data, share results. Download dataset: As a practitioner user, I want to download my data for using it outside the app
- Display dashboard: As a practitioner user, I want a dashboard so I can quickly gain insights into the most important aspects of my data.

3.4 Existing IDM Tools

The analysis of existing IDM tools is made through criteria extracted from the requirements identified before. We identified only three tools: GMD-TOOL DESI (Skoogh et al., 2010), KE tool (Barlas et al. 2016) and DESI (Rodriguez, 2015b). The specific gap between the tools' characteristics and the requirements are presented as follows:
Manage Input Data: All the tools have data loading features, GMD-Tool (Skoogh et al., 2010), and DESI (Rodriguez, 2015b), have features for data collection and use a database for storage. None of the tools has encryption, and versioning features.
Check Data Quality: The comparison of the tools in this criterion showed that only KE Tool (Barlas & Heavey, 2016) has methods for evaluating the input data. None of the tools has features to generate reports on the quality of the input data.
Process Data: it was found that all the tools have features for exporting data, displaying results, and adjusting statistical distributions. GMD-Tool (Skoogh et al., 2010), and DESI (Rodriguez, 2015b) have an user interface. KE Tool (Barlas & Heavey, 2016) and DESI (Rodriguez, 2015b) show graphs of the obtained distributions. Although the KE Tool (Barlas & Heavey, 2016) does not have a user interface, it is possible to generate graphs from the code in the development environment. None of the tools adjust specific distributions such as Markov Chain or evaluate the hypothesis of the properties of the chains.
Software Architecture: KE Tool (Barlas & Heavey, 2016) is the only one that presents diagrams referring to the architecture and implements unit testing to the code. None of the tools introduces a complete solution architecture or uses cloud-based architectures, mainly because they are desktop applications.
Reproducibility: KE Tool (Barlas & Heavey, 2016), is available in a public repository. However, none of the tools is available in the cloud, and they do not have features for sharing data and results obtained.

User Accounts, Manage Projects and Invite User: None of the tools has functional features for managing users and projects or invite users.

4 PRELIMINARY ARCHITECTURE

We present our preliminary solution architecture (see Figure 5) to provide a top-level view of a software's structure representing the principal design and understanding of the problem. The mapping between requirements elicited and described before and the architecture's areas and components is presented in Table 1.

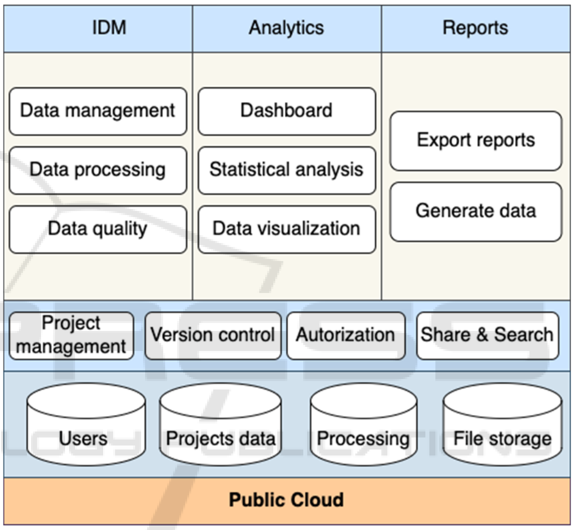

Figure 5: Software architecture.

The main sections of the architecture are described as follows.
Input Data Management: it relates to the input data management requirement described before and includes the following components. Data management: The system should provide a mean to ingest high volumes of data, persist it and store it securely. Data quality: The system must outline data quality issues and provide visualizations and reports to the user. Data processing: The system must process all the data according to the user configuration and apply convenient transformation for analytical purposes.

Table 1: Mapping of requirements and architecture's areas and components.

Area	Component	Requirements
Input Data Management	Data Management	Manage Input Data
	Data Processing	Process Data
	Data Quality	Check Data Quality
Analytics	Dashboard	Display Dashboard
	Statistical Analysis	Process Data
	Data Visualization	Process Data
Reports	Export	Download Dataset, Check Data Quality and Process Data
	Generate Data	Download Dataset
Project	Project Management	Manage projects
	Version Control	Manage Input Data
	Authorization	User accounts
	Share & Search	Invite User and Search Project

Analytics: Dashboard: Dashboards allow the user to quickly gain insights into the critical metrics and information relevant to him. It also provides means for identifying potential issues that require imminent action.
Statistical analysis: It provides summary statistics of variables, fits statistical distributions, estimates parameters, and test goodness of fit hypothesis. Data visualization: Visualization techniques provide to the user a clear representation of information to get quick data insights.
Reports: Export report: It enables the user to have a portable version of the results of the data quality inspection, data processing, and the statistical analysis in html format. Generate data: The platform has to provide the user a mechanism to generate synthetic data that mimic the system's original data according to the statistical distributions of the processes.
Project: Project management: Projects allow the user to organize and centralize the resources, and arrange data, analysis, and reports. Version control: it keeps track of versions of the projects andtheir resources in an organized manner.
Authorization: it allows theadministrator to manage roles and permissions over the project'scontext. It provides a good way to secure files. Share and search: Provide mechanisms for indexing and cataloging data sources and analysis objects in order to facilitate the searching and sharing offiles.
Information: Users: A database dedicated to centralizing user's data, roles, and authorizations. Projects data: A dedicated database for project data management. Processing: All the data are allocated in memory during the processing. File storage: The excepted contents of the system are the original data sources, transformed data, metadata, parameters, results, reports, and synthetic data.

5 CONCLUSIONS

This paper deals with IDM for DES projects in the context of ED overcrowding. To deal with this issue we exploit the real case of the ED of HautePierre Hospital in Strasbourg, France as an experimentation field. From this case, we carried out a statistical analysis of the patient flow and then a requirement analysis to develop a IDM automation tool. The exercise allowed us to analyse this specific IDM process to evidence the needs raised when managing the input data manually without using specialized tools for evaluating data quality, data pre-processing, making statistical analysis and the generation outputs for simulation.

As a result of the experimentation, it was possible to identify some limitations, among which it is worth mentioning the importance of providing rules to validate the data and assess the quality before processing. The validations that need to be done on the data include the revision of variable's names, expected data types, ranges of the variables, presence of null and atypical values, among others. An alternative identified from this process is to perform unit tests on the data, to identify possible errors, and avoid unnecessary processing and erroneous estimations. Moreover, the patient flow events were exported from different data sources and were provided in separate files, which required an additional effort to consolidate them. Hence the first requirement defined is to standardize input file to minimize the time needed for consolidation.

Regarding the statistical analysis, there is a couple of considerations. First, it is important to mention the need to sample enough patient records for several days in order to get a good representation of the process. Second, the number of records considered will impact the statistical methods used for the goodness-of-fit hypothesis tests and the estimation of the transition matrix since these estimates are adequate for certain sample sizes. In the case of estimating the transition probabilities, it is expected that the file contains enough records of the flow of patients so that the transition probabilities can be estimated from the frequencies observed on the event sequences.

From this experimentation we defined the basic requirements for an automated IDM solution for DES model of EDs. Such requirements include managing the input data, verifying the quality of the data, processing and presenting process statistics in dashboards. The preliminary solution consists of an architecture that includes a set of functional automation areas that satisfies these requirements.

As future work, we need to detail the architecture and carry out further developments. To do so, early indications are that the best solution would be to take a microservices approach and to adopt a cloud infrastructure instead of on-premises infrastructure by considering three characteristics of the former model: manageability, scalability, and cost.

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