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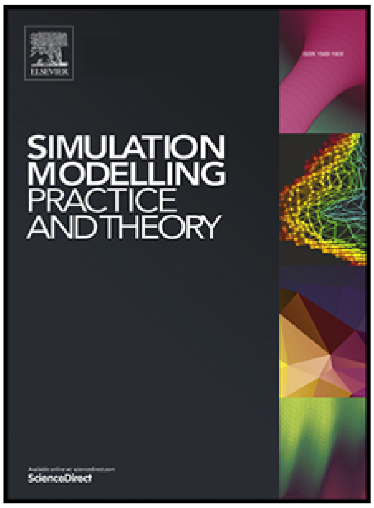

A HYBRID MODEL TO SUPPORT DECISION MAKING IN THE STROKE CLINICAL PATHWAY

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Highlights

- Framework linking Process Mining, Simulation and multicriteria methods in healthcare
- Integrates Process Mining and Simulation supports the development of accurate models
- Improves the decision-making in the stroke's clinical pathway
- Reduces the need for on-site testing during decision-making for process improvements
- Supports Decision-making for clinical pathways in an agile manner

A HYBRID MODEL TO SUPPORT DECISION MAKING IN THE STROKE CLINICAL PATHWAY

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Abstract

Health processes are highly complex and sensitive, requiring continued improvement. Several methodologies have been developed to support these improvement processes, many of which apply Process Mining (PM) to investigate the current states of processes. Some even use Discrete Event Simulation (DES) techniques to explore alternative scenarios. Among the ones using DES, some rely on Multicriteria Decision-Making Methods (MCDM) to guide them in choosing the best scenario, especially in complex decision-making environments. However, no author presents a single framework combining all three techniques mentioned above, to wit, PM, DES, and MCDM. This paper targets developing this combination and exploring its usefulness in guiding process improvement in the health services area. The clinical path for stroke patients, covering from onset of symptoms to hospital discharge, was used as a test case. The research demonstrated that this proposal provided an innovative diagnostic of the process, identifying the activities that should be improved to obtain the most significant results in the process management indicators. Identifying the activities ensures that the impacts of these improvements are indicated with statistical accuracy and eliminating the need to perform on-site testing to test for the best solutions. The research does not address root cause diagnosis of activities to be improved. Therefore, further research needs to be undertaken on an extension of the model to enhance root cause analysis capabilities with a view to validating the framework proposed in other environments and, in this way, assess its replicability.

Keywords

Process mining, Discrete Event Simulation, Stroke, Healthcare, Decision making support, PROMETHEE II method.

1. Introduction

Stroke is currently one of the most severe diseases, being the second leading cause of death worldwide [1]. Stroke events may leave permanent sequelae such as partial paralysis, speech, cognitive, and memory impairments, or even death. However, early-stage symptom diagnosis and the availability of immediate care by specialized teams can drastically minimize impacts [1,2]. Unfortunately, in low and middle-income countries, the burden of stroke is significant and has been increasing with specific care measures remaining inconsistent, placing a challenge for the already stretched healthcare systems [3,4]. As a result, many patients have sequelae that could have been avoided. This is due to the stroke process and the healthcare area being characterized by a high level of complexity involving many issues, such as clinical guidelines, different healthcare systems, and availability of resources, among others [5]. To this end, computer-based techniques are proposed as solutions to overcoming process barriers and enabling managers to obtain meaningful information and focus on improving patient quality of life [6].

When seeking to overcome healthcare issues through process improvements, Process Mining (PM) helps in diagnosing the process by providing a consistent, event log-based process model [7]. PM is a growing area that helps to capture significant findings, e.g., behavior patterns, bottlenecks, and causal relations among activities in process flows. This is done by analyzing processes based on their actual delivery, i.e., using event log information from real data sources, different from methods based in idealized process models alone [8]. Thus, using event data, PM can create process-related information and be used to discover event models, analyze bottlenecks, compare process variants, and so on. This helps to solve business issues [9]. PM in the healthcare area has been used in different case studies with interesting results. For instance, they have been used to ensure that procedures are firmly understood and to increase or monitor a given process's efficiency [10]. To this end, PM can be related to other techniques from data science such as machine learning, predictive analytics, etc., or to process science techniques such as operation management, operation research, and simulation [9].

Simulation is a computational modeling methodology that intuitively and flexibly enables reproducing a given system's dynamics and its complex behaviors considering the interactions among its individual components, populations, and environments [11–13]. In this context, Discrete Event Simulation (DES) is the main simulation method used in the healthcare domain. This technique simulates processes over time and follows entities such as, for instance, individual and dynamic objects that interact with the system's resources. When deploying DES in healthcare processes, simulations usually progress through a discrete time dimension following patients (entities) along procedures (activities) as they occupy and release the system's resources, e.g., doctors, beds, and equipment. The routes covered by entities and the times between activities are described by random value samples taken from parametric and empirical distributions [11–13]. Even though DES can relate risks, activities, and interventions to patients who display their own behaviors, e.g., their own will and individual traits, in real-life applications, constructing and reproducing reality in operational models can be very time-consuming and difficult. So, DES is shown to be a perfect combination with PM, since DES can be used to explore different process changes, and PM enhances building operational models from event log information, leading to simulation results that are more accurate and verifiable [12,14]. Also, [13] point out that several papers propose clinical path management approaches using simulation techniques. For this purpose, decision-makers use DES to carry out "what if" analyses, changing operational scenarios and rules, thus promoting understanding and comparison among key performance indicators in evaluating potential alternatives to be implemented in the processes [14,15].

In healthcare, there may be multiple indicators based on different professional roles (managers, physicians, nurses), points of view, healthcare outcome perspectives (healthcare status, efficiency, safety), etc., and even conflicting targets (maximizing or minimizing) for different criteria [16,17]. For instance, in Emergency Departments (ED), managers deal with different performance indicators to drive improvements while ensuring quality in patient service and treatment delivery processes. These may conflict based on management interests, such as productivity, technology, patient safety, and so on. Through DES, experiments can be carried out to evaluate and compare those indicators in multiple simulated scenarios without interfering in daily operations, [18]. Thus, the best ways to deal with the complex scenarios with multiple indicators, multiple healthcare, and clinical issues have been reviewed with support from multicriteria decision methods (MCDM) [19].

MCDMs are characterized by their capability to handle a range of conflicting goals with each method differing in many dimensions such as how preferences and evaluation criteria are represented, and offsetting factors weighted among the criteria [17]. There are compensatory and non-compensatory methods. In compensatory methods, weak performance in some criteria can be offset by strong performance in other criteria, but the resulting aggregate performance might not reveal weak areas, and non-offsetting techniques cannot do this, while each individual criterion can independently play a crucial role in the aggregate performance [20]. Also, a method can be classified as outranking based on dominance when each criterion's alternatives are compared pairwise. An outranking method can be used for ranking (ordering all alternatives from the worst to the best), sorting (define a reference ordered class for each alternative), and choices (select a subset of acceptable alternatives) [21–23]. In this context, PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) is a familiar popular non-offsetting outranking method used in the healthcare domain, for instance, in ED and hospital services quality [24–27]. In this case, PROMETHEE II is a powerful outranking method providing decision makers with the opportunity to choose among general criterion types depending on the characteristics of the evaluation criteria, e.g., criterion goal (maximization or minimization) and scales (0 to 10, 0 to 1, etc.) [25]. This method can evaluate alternatives, i.e., scenarios that are complex and difficult to compare, or having multiple criteria such as bed occupancy rate, average overall patient length of stay in hospital, etc.; and, as output, provides a complete ranking of alternatives [22,27].

As mentioned above, different techniques are used to assist in the improvement of health processes because of their unique features. PM can transform event records into process models [9,28,29], DES can explore and simulate alternative scenarios [11,30,31], and PROMETHEE II ensures a robust and mathematically-based decision considering different and even conflicting criteria [25,26]. Therefore, such techniques are often combined into hybrid models to take advantage of their complementary strong points [14,26,32]. So, in considering suggesting improvements to the stroke treatment process, where running real life trials is not viable as this could put patients' lives at risk, a hybrid PM, DES, and PROMETHEE II approach is presented that takes the patient's entire clinical journey, process times distribution, resources, and key performance indicators into account. This process is known to be very time-sensitive, both to resources and to the knowledge available in each healthcare unit [33].

To support decision-making in the stroke process, this study proposes the use of PM for process data (flows, times, and resource), DES to create an operational model and explore multiple scenarios, and PROMETHEE II to help suggest improvements with mathematical rigor based on DES output values. The hybrid model is believed to help systematize decision-making processes in the stroke treatment process and provide a robust form of decision-making for process managers during process improvements.

This paper is organized as follows: Section 2 features the study of correlated papers. In Section 3, the proposed method is explained step by step. Section 4 refers to the case study performed applying the proposed framework in a public hospital in Brazil specialized in stroke treatment. Section 5 presents results and discussion, and Section 6 offers conclusions and future work opportunities.

2. Literature Review

Many process improvement proposals for healthcare delivery using PM as a focus are available. [34] formulate a PM-based method for the outpatient analysis processes. In this method, the PM performance analysis approach is used to analyze improvements by applying simulations. By testing this method, the authors were able to prove that 89.01% of the patients are well managed by the hospital and an increase of 10% in the number of patients can significantly increase waiting times. [35] discuss a methodology proposal applied in healthcare processes that applies PM in a goal-oriented manner. The authors tested the proposal to measure the efficiency of the surgery process and showed that it has potential for process improvements. [36] use PM to analyze the stroke healthcare processes and collect insights, indicating that monitoring and treating risk factors can prevent new events from occurring in patients and helped in elaborate policies, plans, and resource allocation for this process. [37] develop and apply a method in the healthcare area that uses PM and a search algorithm to find the optimal process model to maximize reproducibility scores considering the maximum number of nodes and arcs. The researchers applied this method in a stroke event process and identified many patterns that may address some specific issues such as complications stemming from stroke events. [29] propose a method that performs the combination of PM techniques with ontologies to promote customization of process models applied to healthcare. This method, during customization, provides decision-making support for users to ensure customizing the correct structure for processes, and enable improvements in patient treatment through recommendations. The authors used the stroke care process as a case study and found that this proposal can decrease errors during patient treatment.

[38,39] present a successful connection of PM techniques in developing DES models. This relationship, introduced through the framework implemented in ProM6 and connected to Simul8, was used as the hospital setting for the ophthalmological treatment process for cataracts for validating the process. With a view to developing the line of research regarding the combined implementation of PM and DES, an algorithm was applied to adapt ProM6 information to a DES model, and then perform a conformance analysis to study how the knowledge provided by PM techniques can generate robust information for DES in healthcare processes.

[40] refer to the combination of simulation techniques with PM as a means of drafting process redesigns. This combination would be capable of evaluating different improvement alternatives before putting them into practice. To justify this method, a combination is proposed and applied in the purchasing process of a private university.

[41] develop a three-step framework with the objective of leveraging patient visit event data to design healthcare delivery layouts with pod structures. The first phase uses PM to perform a diagnostic of patient flows, the second applies DES to find the optimal size of the pods in the layout, and the third phase applies methods to determine the type of layout to be employed. The research shows that PM is an efficient tool to extract the most significant pathways.

[42–45] use PM as a means of process knowledge and then use DES to study hypotheses and promote improvements to said processes. The authors found that unblocking the ED outflow by in-patients can improve process efficiency more than increasing the ED structure; the optimal output for patients undergoing a stroke event can be increased by improving the capacity of rehabilitative care units. They concluded that the diagnosis process is the bottleneck of the clinical center studied.

[46] propose a technique to develop simulation models automatically based on the healthcare area's event records. For this purpose, they use PM as an input to transform event records into process flows and apply a hybrid model combining DES and Agent-Based Simulation (ABS) to drive business improvements. The case study was performed in patients having cardiovascular diseases to evaluate the impact of medical decisions, for instance, such as implanting a defibrillator. They found that by implanting defibrillators the death rates decrease slightly, but there is a much higher cost increase.

[47], while seeking to solve queue time issues in ED, developed a three-stage framework using PM to find the optimal schedule and reduce waiting times in ED. DES was used to compare the as-is process with the process scheduled using PM. With the optimal scheduling, a reduction of 40% in the waiting times and queue length was achieved.

In addition to combining simulation techniques with PM, many papers combining simulation techniques with other techniques can be found addressing healthcare improvements.[48] discusses the use of hybrid simulation methods in the healthcare domain and shows that this topic has displayed a significant increase in popularity with a rapid development of tools focusing on health and social care applications. For instance, [49] conceptualizes a hybrid simulation framework to combine the integrated deployment of system dynamics and DES for healthcare environments. The case study led the authors to find that the hybrid model suggested was more efficient in capturing behavioral impacts on operational performance.

Also, with regards to hybrid models in healthcare environments, [50] proposes a combination of DES and ABS. According to the authors, this model may be capable of better capturing reality considering the complex structures of queues, flows, human behavior, and decision-making concepts. The model was tested and validated in a radiology center.

[13] present a proposal that develops an orchestration architecture to guide patients' workflow in ED. For this purpose, the authors combine an ABS with optimization algorithms in real-time. This proposal evaluates the ED process and shows that improvements in the performance indicators can be achieved through the dynamic orchestration developed.

[51] use DES to develop a tool to support hospital patient flow management named HESMAD. The tool captures patient flow patterns and provides a visualization of events dynamics and an interface for domain experts. With this proposal, the hospital was able to find the best option, which involves reducing long-term outliers.

[52] uses simulation optimization in a magnetic resonance imaging (MRI) environment to create a patient referral mechanism between two hospitals. This is used to obtain the most feasible number of referral outpatients to minimize the patients' average waiting time or to maximize the revenues of hospitals. The results found can serve as guidelines for collaboration among hospitals.

[53] proposes a reusable method applied to develop simulation models for ambulance systems that consider multiple criteria using DES modelling. The authors point out that the model is comprehensive and easy to use by applying the model in Brazilian and UK systems. They found space for process improvements in both systems.

As mentioned above, the use of multicriteria methods together with simulation techniques shows interesting results. [54] develop a framework that uses Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), a multicriteria decision method to evaluate various correlated performance indicators resulting from experimenting with DES and, thereby, bring improvements to healthcare delivery processes. This study's results show that, when using the appropriate scheduling rules and exploiting the available resources effectively, the best scenario obtained promotes an effective decrease in the orthodontic patient waiting times and lengths of stay.

[18] combines DES as support creating improvement actions with a focus on enhancing management performance and a Decision-Making Trial and Evaluation Laboratory (DEMATEL) to identify the influential and important criteria network used to run the ED in process care in the Brazilian federal government's healthcare system. This combination led to seven improvement actions in resource deployment including technology.

[55] combine DES techniques, Balanced Score Card performance indicators (BSC), and the UTASTAR algorithm to evaluate the effects of reorganizing scenarios on various key performance indicators (KPIs) which were selected by stakeholders to improve the decision-making process through general preference analyses. The authors pointed out that, through the simulation model, stakeholders can evaluate the effects of their decisions on a range of KPIs, where the weighting applied in each KPI was produced by the UTASTAR algorithm.

[26] connect two MCDM techniques to support management decisions when designing improvement actions to reduce ED overcrowding. The author first uses DEMATEL to understand the causal relationship among the patient care criteria. Then, PROMETHEE II was applied to prioritize the improvements based on DEMATEL influencing criteria. As a result, the model developed was easily understood by the ED managers due to its simplicity and usability. The model was also useful in managing resource allocation through a set of improvement actions.

[56] proposes a decision support system combining simulation modeling with MCDM for optimizing dispatching rules to schedule batches on machines in a customer-centric job shop manufacturing system. As output, the authors show that the model provides better outcomes in case of a high level of resource bottlenecks and fluctuation among the customer importance weightings.

In addition, the study of improvements and adaptations to existing techniques was observed. [57] present a method that uses hyperparameter optimization techniques to search among several configurations for the best similarity among the behavior of the Business Process Simulation (BPS) model and the observed event records generating optimized simulation accuracy. This proposal is validated using logs from different domains. [58,59] develop the auto-simulation model builder (ASMB), a framework that applies PM to produce bias-free DES models for healthcare systems and extends the model to enable resource management and provide support in making complex decisions in hospital management. The authors run tests in two scenarios to improve waiting times and queue lengths, with the model results pointing to possible improvements in the reduction of agent waiting times by improving agent cycle time. [60] create the ClearPath method as an extension of the Process Mining Methodology (PM²) with a DES approach that addresses low quality and lack-of-data issues and supports stakeholders' engagement. For this, they apply studies in processes for patients with alcoholism issues, giant cell arthritis, and functional neurological problems. As results of the cases studied it was possible to see the difficulty to obtain robust Electronic Healthcare Records (ERH) data and see alarming variability in cases. [56] propose an adaptation of PM techniques as a support tool in the discovery of knowledge related to healthcare processes in order to contribute to the improvement of this sector in Brazil. As a result, the study found that the hospital key areas (oncology, gynecology, and radiotherapy) that relate to a larger number of areas have a higher chance of failure in interoperability.

Literature shows that PM is used as a method that enables fast learning of process models, measurement of efficacy, identification of bottlenecks and issues, process monitoring, and help in customizing decisions. However, it is also perceptible that this technique suffers when dealing with the search for improved scenarios [29,34–37,61]. For this reason, many authors combine PM with DES, since it has been shown that PM can be used to generate high-quality input data for simulation models, and that these two techniques can be integrated in a fully automated process using logs to create simulation models [38–42,46,58,59]. This combination can also be used to compare simulation models with the as-is process [40,47].

Additionally, simulation techniques can be applied in exploring *what if* scenarios. PM logs usually exhibit many problems, in particular in the healthcare domain. However, researchers have already been exploring these issues [57]. Also, many simulation methods have different problems, e.g., dealing with different types of information and complex decisions. To this end, the authors used hybrid models combining simulation techniques with other ones [48], while looking to capture the process behaviors that cause higher impacts in performance indicators [13,49,50]. To this end, simulation techniques alone do not deal very well with complex decisions such as multiple criteria during prioritizations. Literature shows that MCDM methods can be used to solve these issues. MCDM techniques can evaluate the correlation of DES results [54] or even be used to identify the main parameters and prioritize the best scenarios in those complex situations [18,26,55,56].

Therefore, PM is evidently capable of automatically converting the stroke event log into an accurate process and simulation model, helping in exploring the data for validation purposes. With this simulation model, DES can perform experiments covering a wide range of different scenarios and different levels of granularity according to the business interest drivers. Finally, PROMETHEE II, as an outranking MCDM method due to its unique features, such as its capability for dealing with different objectives, goals, or preference functions, can provide mathematical rigor for decision-makers when prioritizing suggestions for improvements. Consequently, these improvements generate positive results for stroke patients, for example, by reducing the execution time of a given activity, the number of patients who undergo thrombolysis in less than four and half hours can be increased. This is relevant because stroke is a very time-sensitive affliction and must be diagnosed through early-stage symptoms to minimize impacts and prevent leaving permanent sequelae such as partial paralysis, memory impairment, or even death [1,2]. This problem may increase in low and middle-income countries. After all, this process lacks many resources such as consistent process management, and specialized teams, placing additional load on the healthcare system, and resulting in many patients with sequelae that could have been avoided [3–5].

For all these reasons, this paper's study focuses on how managers of a stroke care process can improve delivery for their process activities. The goal of optimizing healthcare delivery in a given context is not sufficient to avoid inequities [62,63]. Stroke places a significant burden on the African descent minority and other ethnic communities [64,65]. Although issues related to providing healthcare on equal terms are not directly addressed in this paper, variables such as race and social characteristics should be considered when performing the quality assessment using the method proposed in leading towards equity in treatment. This study fills the gap in the literature regarding the combination of PM, DES, and MCDM in an end-to-end framework and will enable a more appropriate management of the patient flow and resource allocation. The result of this decision support framework assists in the systematization of the decision making in stroke process improvements, as well as in supporting stroke healthcare managers during complex decision-making processes involving improvement choices.

3. Decision Support Framework

As mentioned above, the healthcare domain is a sensitive environment with complex processes. This leads to the search for continuous improvements looking to achieve better healthcare delivery pathways for patients, as well as processes with lower costs. The development of a DES framework combined with PM and PROMETHEE II techniques is an excellent example for drafting a proposal for continuous improvement in healthcare processes. Interesting results can be obtained by creating a data-based model with the robustness obtained through simulation, without performing on-site testing that might endanger the lives of patients. In this sense, Fig. 1 presents the overview of the proposed framework.

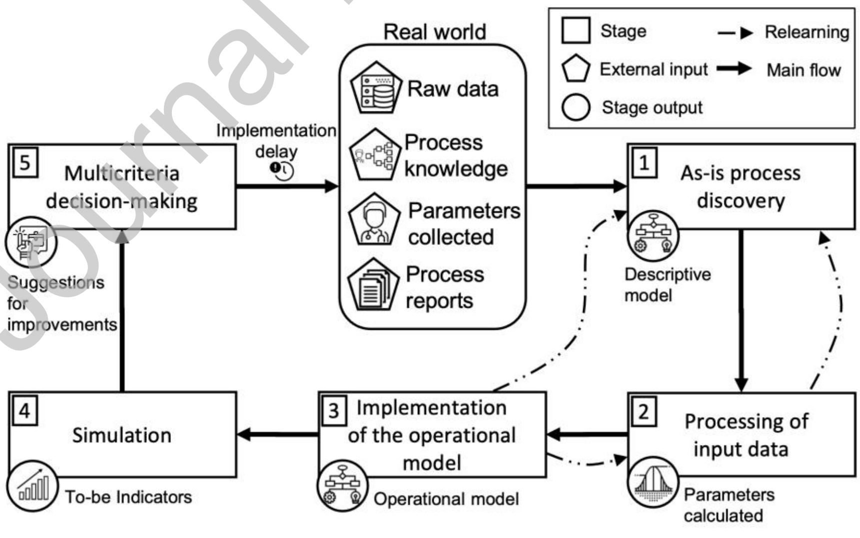


Fig. 1. Framework overview.

The proposed framework can be organized into five sequential steps that interact with each other.

Step (1) "as-is process discovery" targets creating and consolidating a model of the current process, called as-is. This as-is view is created first with PM techniques that discover the process model using the information available in the *event log*. Then, validation is obtained through interactions with domain experts and the as-is model is completed with activities not mapped by PM.

Next, Step (2) “Processing of input data”, refers to the process of collection, investigation, and treatment of all useful data for mapping and parameter setting for the statistical metrics for each process variable. To this end, first PM is used to collect the data available in the *event log,* e.g., activity time probability distributions, queue times, and percentiles of process variants. Then, interactions are carried out with specialists for collecting data on-site in case of information not available in the *log*. Steps 1 and 2 have a very close iterative process, which may need to go back to Step 1 to re-discover the process until process experts and developers are in full agreement. After all this, new activities or process variation metrics are identified showing the need for new collections and time analyses.

Then, Step (3) “Implementation of the operational model” is carried out. In this step, the implementation process for the model drafted in Step 1 is undertaken with the information generated or collected in Step 2 using SimPy [66], a python library for DES. This implementation should be fine-tuned as many times as necessary until a statistically acceptable simulated process is achieved for the current study process.

With the operational model fine-tuned, process (4) “Simulation” of different scenarios is carried out seeking to maximize process indicator outputs. These scenarios are defined from parameter changes to the operational model. These parameters are defined based on the researchers’ and process experts’ experience and tested in order to establish the process indicators that must be improved, and which, consequently, generate process possibilities (to-be) aiming at delivering better outcomes.

Finally, Step 5 “Multicriteria decision-making” takes place. Using the MCDM method PROMETHEE II, an outranking method that addresses the inner relations of each evaluation during the decision process [67], the different to-be scenarios found in the previous step with their respective indicators are evaluated, covering all the indicators required to give suggestions for process modifications. Following that, the changes can be deployed in the real-world process and the framework can be repeated for continuous improvement purposes. The process of deploying the changes in the real world might face delays caused by business issues, such as prioritizing other improvements, periods of high occupation and workloads in the hospital.

4. Application

As explained above, this framework can be described in five main steps. Therefore, this section will describe the execution of these stages in the stroke treatment care process at a public hospital specialized in stroke treatment in Brazil.

4.1. Discovery of the as-is process

The first stage of this framework, as shown in Fig. 2, has two main objectives: i) understand the current process (as-is) and ii) visually model this process for study purposes. PM plays a fundamental role in enabling a first-level process analysis using documental information. However, for this case, the model discovered using PM, although supportive for understanding the scenario under evaluation, does not meet the granularity of data required for running a simulation of this process.

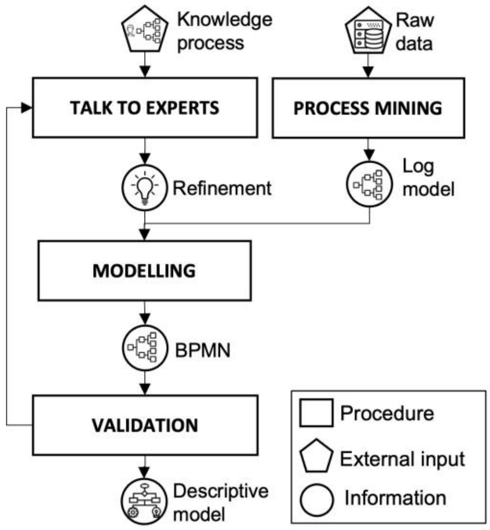


Fig. 2. As-is process discovery flow.

A long iterative mapping process was carried out with four process specialists (two nurses, one doctor, and one process manager) from the Joinville Stroke Registry (JOINVASC) to construct a descriptive model of the activities involved. Due to the COVID-19 constraints, this mapping process was performed through weekly remote meetings over a two-month cycle. Each meeting lasted for about one hour and generated approximately four hours of studies prior to the next meeting. Also, in general, the meetings were held by the authors with the two nurses, and, when specific topics were analyzed, the doctor or the process manager would be called in. For instance, the meeting to provide understanding of neurologic evaluations was also attended by the doctor. The model was drafted and refined at the end of the iteration process applying *Business Process Management Notation (*BPMN) to apply a language understandable by process experts and still translatable into modeling for simulation technicians.

The BPMN model shown in Fig. 3 represents the as-is process in a study that was validated with the same hospital specialists who helped in constructing the descriptive model. This step validated only the BPMN logical process. This model, together with probability distributions, time parameters, and patient classifications covering patient journey variations, targets establishing a model to be implemented in the simulation.

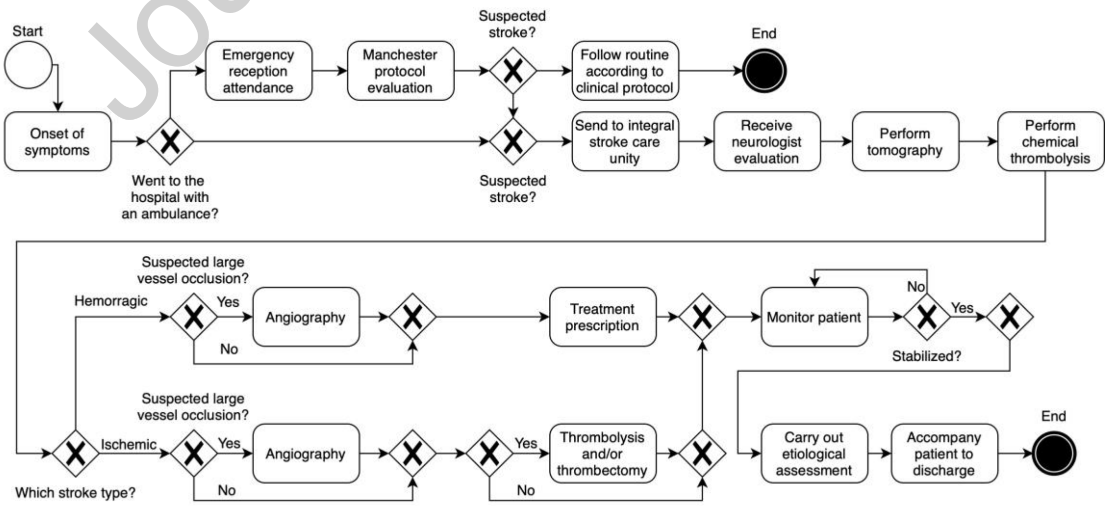


Fig. 3. Descriptive model in BPMN.

4.2. Collection and processing of input data

Next, the data collection and the treatment stages have two focus items: i) establishing the statistical distributions of the time used in each activity in this process and ii) the classification used on patients that drive variations in the process. As per Fig. 4, this stage occurred in two steps. For the data available in the raw process data set, first a cleaning and filtering process of relevant data was performed, followed by PM operations and statistical data analysis.

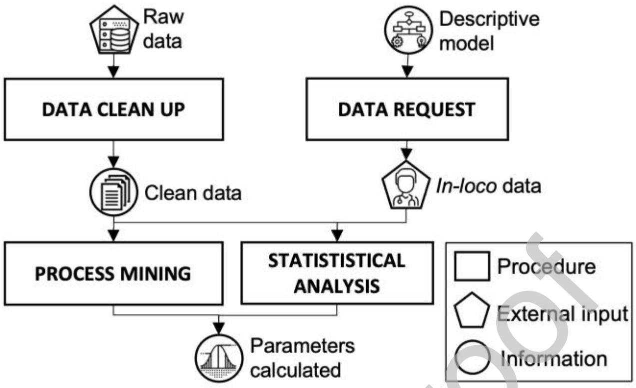


Fig. 4. Processing of the input data flow.

Process Mining (PM) is a relatively new research discipline that can be a valuable strategy to uncover the actual processes, like patient pathways, verify compliance of health practices, and obtain insights on bottlenecks by extracting knowledge from event logs. These event logs are obtained from data stored in databases, such as healthcare information systems, enabling the discovery of the healthcare processes (or clinical pathways). An event log can be viewed as a set of traces, each containing activities executed for a particular process instance, and may come from more than a single source of information [9,10] (for a recent survey on process mining applications see [56]).

In process mining terminology, an event is characterized by various properties, such as timestamp, resource identifying the executor, associated costs, etc. Each event must be associated with a case. In healthcare, dealing with some form of patient identification is usual in identifying the case (stored in electronic health records). When all the events in a case are in chronological order, a trace (a finite non-empty sequence of events, such that each event appears only once, and time is non-decreasing) is established. Having various cases that follow the same trace is possible, but each case is different. An event log is defined as a set of traces. In theory, any process that has a time dimension could be stored as an event log database. Fig.5 shows an event log segment used in this paper.

Case ID	Activity	Complete Timestamp	Variant	Sex	Hospital	Banford	NIH
1017030201	Beginning of symptoms	00:00.0	Variant 1	M	Outros	POCS	1
1017030201	Assistance	00:00.0	Variant 1	M	Outros	POCS	1
1017030201	Hospital admission	00:00.0	Variant 1	M	Outros	POCS	1
1017030201	CT scan	09:00.0	Variant 1	M	Outros	POCS	1
1017030201	Discharge	59:00.0	Variant 1	M	Outros	POCS	1
2009111003	Beginning of symptoms	00:00.0	Variant 2	M	HDH	POCS	5
2009111003	Assistance	00:00.0	Variant 2	M	HDH	POCS	5
2009111003	Hospital admission	49:00.0	Variant 2	M	HDH	POCS	5
2009111003	Discharge	59:00.0	Variant 2	M	HDH	POCS	5
2009122503	Beginning of symptoms	00:00.0	Variant 2	M	HMSJ	TACS	6
2009122503	Assistance	00:00.0	Variant 2	M	HMSJ	TACS	6
2009122503	Hospital admission	23:00.0	Variant 2	M	HMSJ	TACS	6
2009122503	Discharge	59:00.0	Variant 2	M	HMSJ	TACS	6
2010010201	Beginning of symptoms	00:00.0	Variant 2	F	HMSJ	PACS	6
2010010201	Assistance	25:00.0	Variant 2	F	HMSJ	PACS	6
2010010201	Hospital admission	15:00.0	Variant 2	F	HMSJ	PACS	6
2010010201	Discharge	59:00.0	Variant 2	F	HMSJ	PACS	6

Fig.5. Event log sample.

For the unavailable data, on-the-spot collections were requested based on the needs of the descriptive model found in Step 1 with respect to the mean, minimum, and maximum scans of the times for statistical approximations to enable building the model.

Thus, together with the iterations performed in the model development stage, the necessary information was collected at different times. The data collected from the raw process data enabled, first, a macro view of the process, as shown in Fig. 6, representing the model developed jointly with specialists and the model found during PM evaluations. In this figure, a pattern that can be organized in 6 stages can be perceived:

- Stage 1 – The start is the onset of symptoms in the patient;
- Stage 2 – The patient moves on to the medical support stage, covering the process of receiving in the hospital patients capable of unaided displacement or arriving by ambulance and classifying the respective stroke levels according to the Manchester protocol;
- Stage 3 - This is followed by hospital admission, with the patient being referred to the Integral Stroke Care (ISC) sector and once there, being evaluated by a neurologist;
- Stage 4 - The Computer Tomography (CT scan) is performed to evaluate brain blood clot status;
- Stage 5 - The treatment is provided based on the diagnostic established in the previous stage to deliver the appropriate care to the patient.
- Stage 6 - Finally, an etiological assessment is performed, wherein the etiological assessment of stroke is undertaken with a view to identifying the cause. The patient is then discharged.

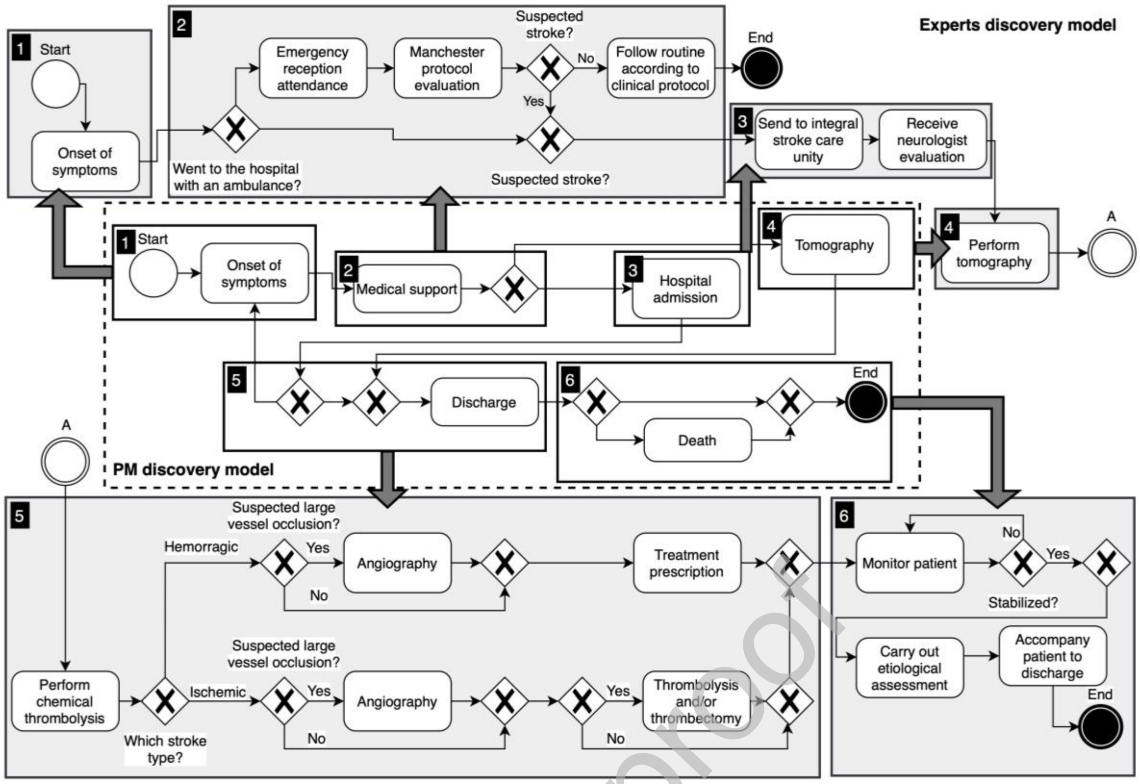


Fig. 6. Comparison of the process discovered and the one developed with experts in BPMN.

Thus, in comparing the process discovered by applying PM to the raw data with the descriptive model drafted jointly with experts in Stage 1, it is remarkable that the model found has a higher granularity in relation to the one required for simulation. This may be highlighted by Stage 5, which is not even portrayed in the model discovered with PM and by Stage 4, which displays a drastic difference in the information presented.

Consequently, this makes it difficult to design the actions required to promote improvements to the process. Therefore, several on-the-spot processes of data collection had to be performed to adapt the information to the simulated model. In the event of needing raw data, it could be collected through PM:

- The onset of symptoms until admission at a hospital (symptom-to-door); and
- The duration of CT scans;

Additionally, some fundamental process variation classifications could also be collected:

- Percentile of patients arriving by transport at the hospital;
- Percentile of patients with suspected large vessel occlusion; and
- Percentile of patients requiring stroke treatment.

On the other hand, it is worth mentioning that several other activities were partially represented in the log. However, these have not been at a level of granularity sufficient to turn the data available into useful information for simulation purposes. So, using the log with purely statistical data analysis techniques has enabled collecting the following data:

- Interval between arrivals of new patients with symptoms;
- Duration of patient hospital permanence; and
- Percentile of patients by type of stroke.

The other time and resource information required, despite this resulting in a data model with lower reliability, were collected with the help of process specialists, and then statistical adjustments were made. With this, Table 1 displays the view of the parameters obtained for each step of the process.

Table 1
Process parameters.

Id	Stage	Flow		Time (in minutes)				Target
		Previous	Successors	Distribution	Mean	Max	Min	
1	Onset of symptoms	-	2,6	Exponential	576			
2	Admission queue	1	3					
3	Emergency reception admittance	2	4	Triangular	180	2700	0	
4	Manchester classification queue	3	5				1	
5	Manchester classification	4	8	Triangular	5	17	0	94% -> 8
6	Wait for ambulance	1	7					
7	Ambulance transportation	7	8	Triangular	71.4	129	32	
8	Wait for bed	5,7	9				3	
9	Transfer to ISC	8	10	Triangular	5	18	1	
10	Neurologist evaluation queue	9	11				1	
11	Neurologist evaluation	10	12	Triangular	13	22	1	
12	CT Scan queue	11	13				1	
13	CT Scan	12	14,16,18	Triangular	4	10	3	33% --> 14, 33% --> 16, 33% --> 18
14	Angiography queue	13	15				12	
15	Angiography	14	16,18,20	Triangular	45	78	45	5% -->16, 95% -->18
16	Treatment prescription queue	13	17				3	
17	Treatment prescription	16	20	Triangular	7	15	3	
18	Thrombolysis queue	13,15	19				2	
19	Thrombolysis	18	20	Triangular	60	61.2	60	
20	Etiological assessment queue	17,19	21				1	
21	Etiological assessment	20	22	Gauss	14062	S.d->	13599	
22	Discharge	22	-					
Resources					Start of use		End of use	Quantity
1	Bed		Start in stage: 9	9	Ends in stage:		22	30

Each stage of the process (regardless of being activity or queue, i.e., waiting time) with their respective predecessors and successors and their statistical times is shown. When outputs are different, the percentages used for targeting the flows are also displayed. For example, from the CT scan activity, 33% of patients go to the angiography queue, 33% to the treatment prescription queue and 33% go to the thrombolysis queue.

For queues, the minimum time patients spend in them is shown. In general, the patient queueing time is mostly ruled by the availability to perform the activities. The values for these times were collected on the spot by the nurses. For activities, the time distribution curve for the activity is shown. Thus, it is worth mentioning that the times and curves from activities of “Onset of Symptoms" and "Etiological assessment" were collected based on the event log, so they display their own distributions and parameters. For these activities, statistical tests with continuous statistical distributions were performed with the most adherent being, respectively, exponential and Gauss. The other activities, i.e., the ones with triangular distribution, were set with this distribution because the data needed were unavailable. Therefore, the nurses were interviewed, and their empirical knowledge used to set minimum, mean, and maximum values. In addition, the bed resource stands out as the main one throughout the in-patient treatment journey. The availability of this resource was reported by the nurses. Therefore, this resource is allocated to a patient (*p)* when being referred to the stroke treatment unit and the same resource remains to be allocated to that patient until his or her discharge.

4.3. Implementation of the operational model

Then, with the previous steps completed, the development of the operational model is carried out. This is nothing more than a version of the as-is process (see Fig. 6) represented within simulation engines whose (P) parameters (see Table 1) are input data that guide the pace of the simulation and generate (I) indicators that measure the process. The results of these indicators should be statistically significant to enable exploration of *what if* scenarios. Thus, this development, as shown in Fig. 7, has five procedures for achieving this alignment.

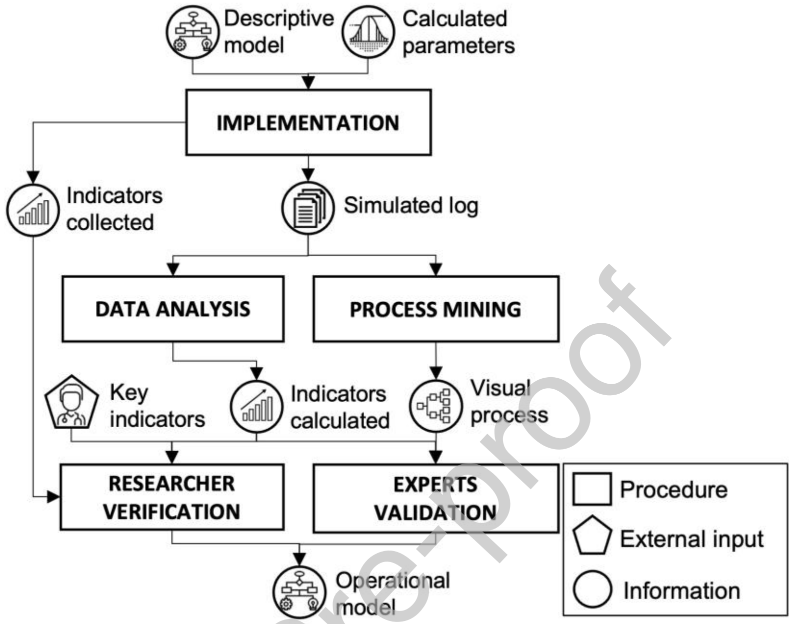
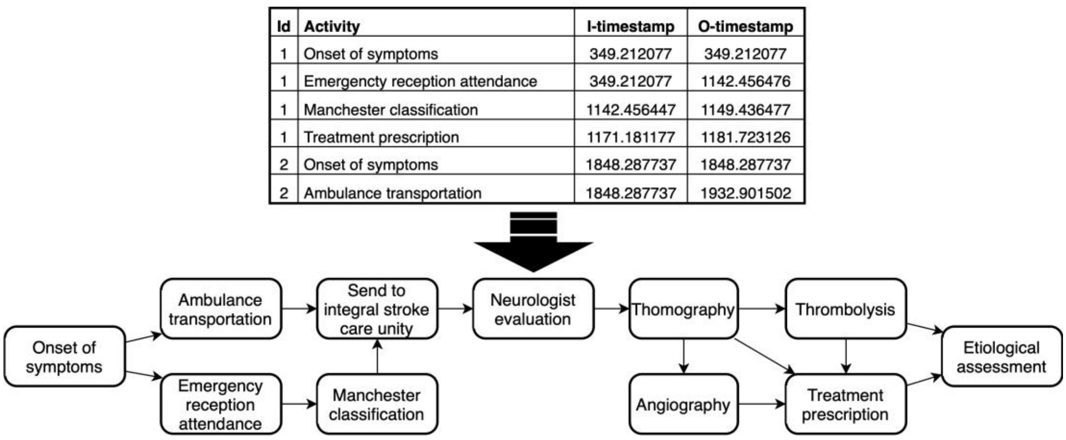


Fig. 7. Implementation of a simulated model flow.

For this purpose, using the SimPy library of DES in Python, first the combination is performed for the model developed in BPMN (see Fig. 3) with the consolidated data (see Table 1), which expresses the understanding of the process by the experts with the level of data granularity desired for simulation.

To validate this combination, qualitative alignment, to check whether the process logic simulated was identical to the descriptive process, and quantitative alignment, to understand the model similarity steps, were undertaken. This validation was performed with the same nurses mentioned in Step 1 (See Section 4.1). In the qualitative evaluation, according to Fig. 8, the log generated from the simulation was transformed into a visual flow with PM techniques and was presented to the specialists to validate the simulation as compared with the BPMN which represents the as-is process (see Fig. 3).



Id	Activity	I-timestamp	O-timestamp
1	Onset of symptoms	349.212077	349.212077
1	Emergencty reception attendance	349.212077	1142.456476
1	Manchester classification	1142.456447	1149.436477
1	Treatment prescription	1171.181177	1181.723126
2	Onset of symptoms	1848.287737	1848.287737
2	Ambulance transportation	1848.287737	1932.901502

Fig. 8. Operational Model in PM visual flow.

For the quantitative evaluation, indicators (*I*) of interest were collected from the experts that, at that moment, are used to evaluate whether the operational model is capable of reflecting reality with the precision desired. Two indicators were chosen: average bed occupancy, for reflecting the use of the main resource in the process and the average total length of hospital stay, for reflecting the duration of the patient journey in the stroke process.

To establish the average bed occupancy (I1 or $\bar{T}$), the sum of the occupancy rate in each day (Or_i) was calculated over the n days of simulation. The value of Or_i is obtained by dividing the sum of (Z_{pi}) for each patient p over the number of beds available L on day i. Where $Z_{pi} = 1$ if on day i, patient p was between the moment he or she was referred to the integral stroke care unit (ISC_p^I) and the moment of discharge D_p^O, otherwise $Z_{pi} = 0$. This is expressed by equation (1):

$$I1 \text{ (or } \bar{T}) = \frac{\sum_{i=1}^{n} Or_i}{n} \quad where$$
$$Or_i = \frac{\sum_{p=1}^{P} Z_{pi}}{L} \ \forall \text{ i } where \qquad (1)$$
$$\begin{cases} Z_{pi} = 1, if\ ISC_p^I \leq n \leq D_p^O \\ Z_{pi} = 0, \ \ c.c \end{cases}$$

This calculation, although simple, has a specific complicating factor. For specialists, on a day-to-day basis, this can be calculated simply by evaluating the number of patients undergoing the process and the number of beds available on that day. The calculation performed in the simulated models is naturally more accurate because of considering the exact time (minute) that each of the beds was occupied. For example, if one patient leaves at 3:00 a.m. and another arrives in at 3:00 p.m., for simulation purposes, one bed would be occupied, whereas, for the process team, two beds would be occupied.

Thus, as regarding the fact that the simulation can produce more granular information about the occupation rate due to the level of granularity of its information, i.e., the simulation is measured by minute, whereas the actual hospital is only able to measure it by day; and given that the simulation is being compared with reality to validate the operational model, the information and the data must be aligned at the same level of granularity to check whether results of the simulation are statistically significant. To enable aligning this indicator, an adaptation was performed that would enable evaluating how many patients were in hospital on each day, disregarding the length of their stay there.

With this indicator, first the definition of the warm-up period of the model was defined. This period has the function of taking the use of resources and times of activities to a stable level, similar to the actual values. It should be excluded from the analysis for obtaining more consistent indicators. The Welch method [69], which has been used in healthcare [70,71] was used to identify the warm-up period. First, the method plots a moving average with a window of *w* days, based on the mean of *n* replications for the length of *m* days. Then, as a graphical model, users can decide on the convergence point, i.e., where the model stabilizes.

For this case, the bed occupancy rate (main resource) was used to evaluate the warm-up. For the parameters, the values of m = 100 days were enough to understand where the model stabilizes; w = 5 days of window to obtain a smooth graph, and n = 10 replications to have a reasonable approximation. The moving average for the Welch method and the real times of occupancy rate and its mean were represented in Fig. 9.

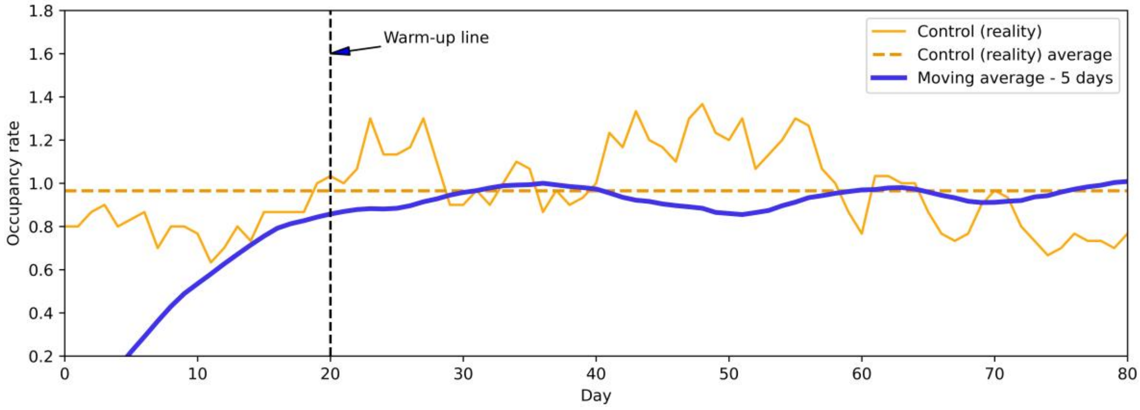


Fig. 9. Warm-up analysis.

Therefore, it is noticeable that on day 20 the model reaches the base level of the model oscillation; it appears to converge, and it is close to the control (reality) mean occupancy rate. Thus, days 0 through 19 will be considered the warm-up period and excluded from the analysis.

In this section, the indicator was evaluated in comparison with the control data obtained from the hospital logs, according to Fig. 10. With this figure, the simulation presented can be seen to display a match in behavior when compared to the control data (reality). The mean values are summarized in Table 2.

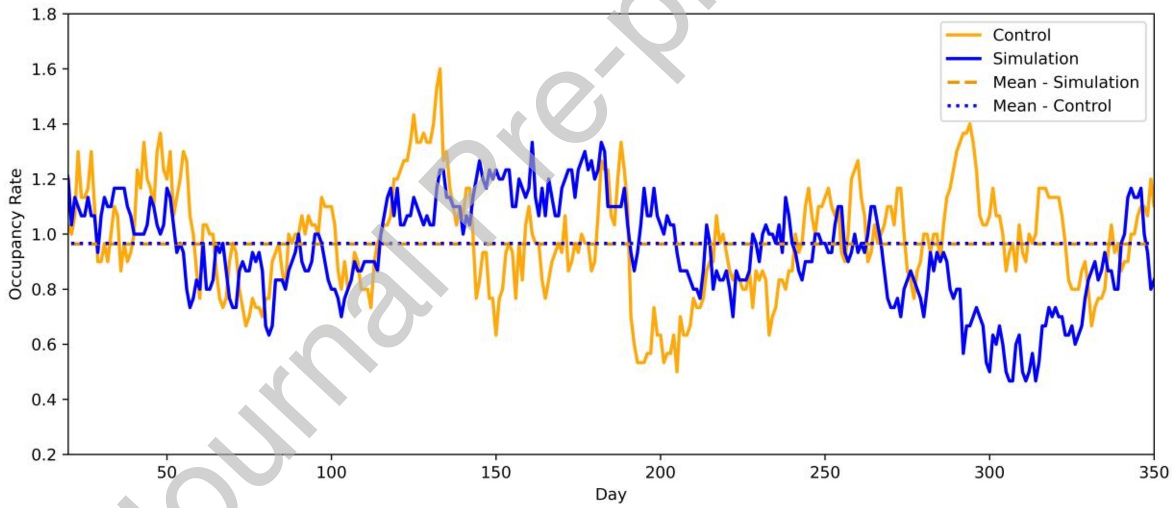


Fig. 10. Bed occupancy rate by days.

Table 2
Comparison of bed occupancy rate (*I1*).

	Control	Simulation
Confidence Interval	96.64 (±2.2) %	96.17 (±2.3) %

Some points must be highlighted regarding the warm-up analysis and the bed occupancy rate by days (see Fig 9 and Fig 10). In some points, the simulation can be seen to go out of sync with reality, but this behavior can be explained. For instance, in Figure 9, between days 50 and 80 and, in Figure 10, between days 280 and 320, this happens because the etiological assessment has a Gaussian distribution and a high value of standard deviation (see Table 1) and its random pattern during the simulation can lead to that difference. Also, as mentioned above, the real environment is very complex, e.g., featuring a multiplicity of resources, clinical guidelines, and employees, and is not fully integrated by systems, frequently leading to requiring help from experts to collect data or information on site. This makes it nearly impossible to inspect all process parameters which, in its turn, renders the simulation a simplified version of the reality, with the resulting difficulty in achieving highly accurate simulation. Nonetheless, in general, the mean values and the range of occupancy rate are perceptibly relatable.

For Indicator *I2*, the average of the patients' hospital permanence time is calculated. This calculation considers the time interval for each patient from referral to the ISC (ISC_p^I) until discharge (end of etiological assessment activity) (D_p^O). Then, the mean is calculated, applying Equation (2):

$$I2 = \sum_{i=1}^{p}(ISC_p^I - D_p^O)/p \quad (2)$$

The result obtained was compared with the times calculated in the original event logs, generating the values presented in Table 3.

Table 3
Comparison of average length of hospital stay (*I2*).

	Control	Simulation
Mean	10.78 (±0.40) days	12.41 (±0.44) days

The results obtained for indicator I2 were not as satisfactory as those for Indicator I1. However, this value is acceptable for two reasons. First, as can be seen in Fig. 9 and Table 1 and was mentioned above, the "etiological assessment" activity exhibits a high level of variation over time. This might generate distortions in the mean values calculated, and these distortions may become noticeable when conducting multiple simulation runs with different random seeds. However, these results were presented to the process experts for validation and to determine whether this level of accuracy was satisfactory, and was validated and approved. After all, even if the quality of the data available in the hospital may not be perfect and have some inconsistencies leading to some deviation in the values presented, these values are close enough to feature a match in behavior with the control data. Thus, these results can be accepted, and the construction step of the operating model can be considered as completed.

4.4. Simulation

The simulation step is performed seeking to create to-be versions of the process from simulation using the combination of model input parameters (*P*) (quantity of resources, process times, etc.) at values different from today. Thus, each simulated scenario generates different results for the indicators (*I*) used to evaluate the process. This step is organized into two procedures: i) filtering of process indicators and ii) testing scenarios, as shown in Fig. 11.

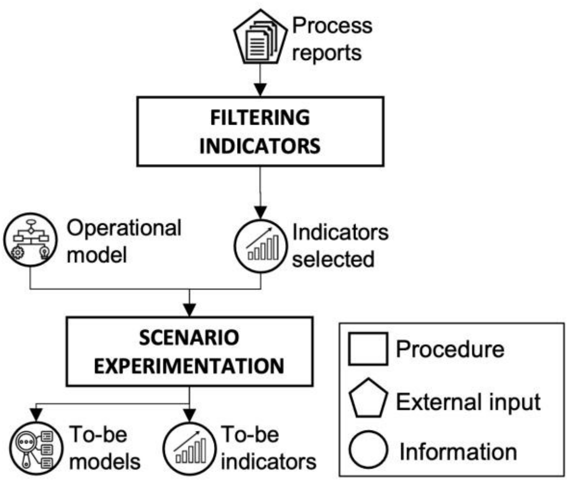


Fig. 11. Simulations stage flow.

The first procedure, "filtering indicators" is dedicated to an analysis, using the hospital management reports, to identify all the main process indicators. The reports were used to identify the indicators for analysis because of two main reasons; first, as this proposal seeks to help managers make decisions for process improvements, the task might become more practical and easier for them, if they have simulation indicators exactly like the ones they already use to manage the process. Also, those indicators in the management reports are built considering many important features for the hospital, e.g., clinical guidelines, government metrics monitoring performed by the internal research group. Therefore, those indicators are very meaningful for the process management and could be used in the simulation. Thus, this procedure was a key because there are numerous indicators in this report that, in terms of business, serve to answer different questions for different stakeholders in the process. Many of these indicators end up being redundant or outside the scope of the proposal being studied, as shown in Table 4.

Table 4
Stroke indicators.

Id.	Indicator	Usage Decision	Justification
1	Bed occupancy rate	Relevant to the process	One of the main bottlenecks of the most important process and resource
2	Percentage of transient ischemic stroke attended compared to total stroke	Outside the scope of the process	Evaluates information that is not a process performance metrics
3	Percentage of patients seen at the integral stroke unit	Outside the scope of the process	The simulated environment only covers services provided in the Integral Stroke Unit
4	Number of patients with time door – tomography (CT) of patients with stroke < 25 minutes and with onset of symptoms < 24 hours	Outside the scope of the process	Symptom onset time until admittance is not controllable by simulation
5	Number of patients with time door – tomography (CT) of patients with stroke < 25 minutes and with onset of symptoms < 6 hours	Outside the scope of the process	Symptom onset time until admittance is not controllable by simulation
6	Average time door – tomography	Excluded by redundancy	Indicator 6 corresponds to a fraction of the time of indicator 7.
7	Average time door – needle	Relevant to the process	One of the main process indicators and measured by the simulation
8	Average overall length of stay	Relevant to the process	One of the main process indicators and measured by the simulation
9	Number of patients with needle port time of stroke patients < 60 minutes	Relevant to the process	One of the main process indicators and measured by the simulation
10	Total thrombolysis vs total thrombectomy	Outside the scope of the process	Evaluates information that is not being evaluated in the simulation
11	Percentage by types of complications in stroke patients	Outside the scope of the process	Evaluates information that is not being evaluated in the simulation
12	Hospital mortality due to stroke	Outside the scope of the process	Evaluates information that is not being evaluated in the simulation
13	Hospital discharge with referral to basic health unit (UBS)	Outside the scope of the process	The simulated environment only covers services delivered in the Integral Stroke Unit
14	Medications prescribed in high according to stroke subtype	Outside the scope of the process	Evaluates information that is not being evaluated in the simulation
15	Percentage of patients who received physiotherapy assessment in 48 hours by total stroke population	Outside the scope of the process	Evaluates information that is not being evaluated in the simulation
16	Percentage of patients who received 48-hour speech therapy evaluation by total stroke population	Outside the scope of the process	Evaluates information that is not being evaluated in the simulation

Thus, in addition to the two indicators of interest already raised with the experts (*I1* and *I2*), two other indicators (*I3* and *I4*) were chosen to measure the improvement scenarios, and the indicators can be summarized in:

- *I1* – Bed occupancy rate;

- *I2* – Average overall stay;
- *I3* – Average time door – needle; and
- *I4* – Percentage of patients with time door-needle ≤ 60 minutes.

The last procedure of this stage is reached and refers to the process of testing the model. This stage includes phases i) identify the model parameters that drive changes to indicators; ii) draft project experiments; and iii) carry out the experiments.

Phase I. "Identify in the model the parameters (*P*) that drive changes to indicators (*I*)". To this end, a process of sensitivity tests in the parameters of the operational model, a study that involves the knowledge developed throughout the creation of the project, and the assessments of the model itself are used. This phase identified the main process parameters to be changed as the number of beds available – because this is the main resource, and the mean etiological stroke assessment time – for being the longest activity of the process and, therefore, increased times keep patients in hospital longer. The parameter levels to be tested for each parameter were defined, as shown in Table 5.

Table 5
Main parameters influencing the process and their evaluated levels.

Main parameters		Levels			
Pi	Parameter	As-is	Min	Max	Jump
P1	Beds available	30	20	30	-5
P2	Mean time etiological assessment	14062	7200	14062	-3340.5

The values of the levels were decided based on how the hospital could be modified to achieve improvements. These decisions were guided by the analytical view of the researchers' process knowledge and the experience of process specialists.

Thus, for parameter *P1* "Beds available", the understanding is that it is not necessary to reduce the rate of occupancy of beds to low values to the point of always having vacant beds. After all, beds permanently vacant could be occupied by other subdivisions of the hospital, e.g., emergency department or COVID-19. Therefore, for this case, a reduction of up to 33% (from 30 to 20 beds) of the bed contingent will be studied, with a view to finding the best number of beds for this process given the suggested changes.

Concerning parameter *P2* "Mean etiological assessment time", while the period in the hospital being studied takes about 9.5 days (14,062 minutes), in private hospitals the same procedure occurs in up to three days and only cases with complications have longer timeframes. Therefore, in conversations with experts, studying reduction down to 5 days (7,200 minutes) is enough. With this, the following sets are established:

- P1 = {30, 25, 20}
- P2 = {14062, 10631, 7200}

Each combination of values in the above sets creates a scenario (C_i), for example, scenario (C_2) is {P1:30; P2:10631}. Scenario (C_1)={P1:30; P2:14062} represents the as-is process and evaluates whether the best configuration would be maintaining the current process. The other scenarios represent possible configurations for improving the process.

Then, Procedure II is drafted. The indicators selected as relevant for measuring scenarios *I1*, *I2*, *I3* and *I4* are developed and integrated into the simulation process. Indicators *I1* and *I2* have already been developed to align the process in Section 4.3 with the Equations (1) and (2).

Indicator *I1*, even if already developed, needs an adaptation to ensure that the improvements found are in accordance with the business rules defined by the hospital. Their calculation expresses a binary indicator $I1b$ indicating whether the value of the average rate $\bar{T}$ previously calculated as *I1* is less than or equal to 95% and greater than or equal to 75%, according to Equation (3).

$$\begin{cases} I1b = 1, if\ 0.75 \leq \bar{T}\ \leq\ 0.95 \\ I1b = 0,\ \ c.c \end{cases} \quad (3)$$

The decision for these two values (95% and 75%) has been taken, because the overflow of these values represents, respectively, an overcrowding and an excessive vacancy of beds that could have been better allocated.

For indicator *I3*, the average time interval that each patient p took from arrival at the hospital to the onset of treatment Y_p is calculated using Equation (4):

$$I3 = \sum_{i=1}^{p} Y_p\ /p \quad (4)$$

For each process variant, either with the arrival of patient *p* at reception At_p^I arriving by independent means, by direct arrival at the Integral Stroke Unit ISC_p^I by ambulance, or with the onset of treatment being angiography An_p^I or thrombolysis T_p^I, Table 6 explains each of the calculations used in each variation.

Table 6

Calculation table of each process Y_p variation.

Description	Formula
If patient arrived at reception At_p^I arriving by independent means and needing angiography An_p^I. (4.1)	$Y_p = An_p^I - At_p^I$ (4.1)
If patient arrived at reception At_p^I arriving by independent means and going straight to thrombolysis T_p^I. (4.2)	$Y_p = T_p^I - At_p^I$ (4.2)
If patient arrived by ambulance, being referred directly to the Integral Stroke Unity ISC_p^I and needing angiography An_p^I. (4.3)	$Y_p = An_p^I - ISC_p^I$ (4.3)
If patient arrived by ambulance, being referred directly to the Integral Stroke Unity ISC_p^I and straight into thrombolysis T_p^I. (4.4)	$Y_p = T_p^I - ISC_p^I$ (4.4)

For indicators *I4 and I3* calculations are used, and the count is performed for (*p*) patients who had time intervals of less than 60 minutes from arrival in hospital and going to the thrombolysis process. This calculation can be represented by Equation (5):

$$I4 = \sum W_p\ \ \forall\, p\ \ where$$
$$\begin{cases} W_p = 1, if\ Y_p \leq 60\ minutes \\ W_p = 0, c.c \end{cases} \quad (5)$$

In the final step, each simulated scenario is performed with n replications to obtain the response values for *I1, I2, I3,* and *I4* within a predefined confidence interval (*CI*) of 95%. The n value of the replications is calculated from the maximum value n_i^* necessary for all indicators to fit within the *CI* represented by Equation (6) as [67]:

$$n = \max(n_i^*)\ \ \ where,$$
$$n_i^*\ =\ (\frac{t_{n-1,\frac{\alpha}{2}}\, S/\sqrt{n}}{h_i^*})^2\ \forall\, i \quad (6)$$

For this evaluation, a test with 15 replications for the as-is process is carried out to measure whether *n* = 15 is a sufficient value to achieve the *CI* = 95% given the target accuracy for each indicator. As per Table 7, indicator *I1* for accuracy calculation is being used in its original (fractional) form.

Table 7

Analysis of the number of necessary replications.

I.	Standard deviation (S)	Target accuracy (h_i^*)	n_i^*	$n_i^* \sim$
I1	0.0418	±0.02 %	1.34	2
I2	634.71	±720 min	0.23	1
I3	495.98	±90 min	9.31	10
I4	0.0178	±0.02 %	0.24	1

I3 can be seen to require the highest number of tests (n = 10) among the indicators, which is the minimum number of experiments for this case. As the number of trials with n = 15 has been tested, the maximum value will be maintained bringing a higher accuracy to the results. Thus, Table 8 summarizes the results of the simulated indicators in each scenario with 15 replications.

Table 8
Indicators simulated by scenario.

	Scenario C_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
	P1	30	30	30	25	25	25	20	20	20
	P2	14062	10631	7200	14062	10631	7200	14062	10631	7200
I1b	Value	1	1	1	0	0	1	0	0	0
I2	*CI*	351,53	214,72	136,13	5315,97	3013,78	376,68	6285,70	9535,06	6585,87
	Mean	17841,22	14318,97	12290,42	47081,85	19322,00	12889,45	103448,86	71308,44	37451,57
I3	*CI*	274,69	119,54	57,24	5338,89	2981,14	260,81	6361,57	9495,49	6550,49
	Mean	2447,34	860,11	602,21	32461,05	6011,85	1217,11	90128,29	59162,13	26280,01
I4	*CI*	0,010	0,018	0,009	0,013	0,026	0,025	0,014	0,016	0,013
	Mean	0,490	0,594	0,637	0,423	0,443	0,557	0,534	0,467	0,416

Therefore, since there are multiple scenarios to be evaluated with indicators addressing different objectives and with different numerical scales, the use of MCDM is fundamental for the decision-making in improving this process.

4.5. Multicriteria decision-making

The last part of this proposal refers to the selection of the improvement that should be made to the process being analyzed. To this end, the data obtained from the simulation of scenarios performed are used, followed by a study undertaken to understand the weightings that each indicator should receive. A multicriteria decision support technique is applied to guide these decisions, as shown in Fig. 12.

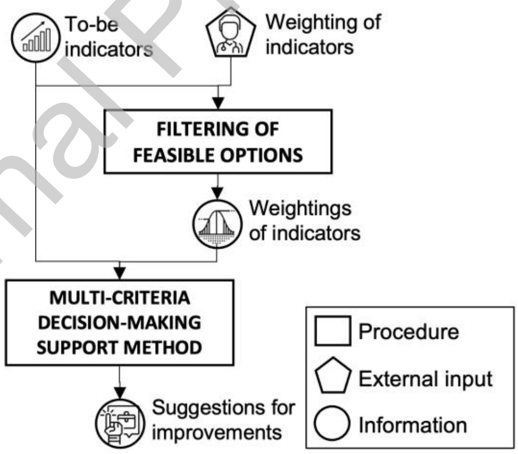


Fig. 12. Multi-criteria decision-making flow.

First, to choose the best improvement scenarios among those evaluated, the weighting to be allocated to each of the indicators *I1b, I2, I3,* and *I4* must be evaluated. At this moment, initially just the scenarios where *I1b = 1* can be selected*, i.e.,* the feasible scenarios; and merely evaluated the other indicators in MCDM or allowed MCDM to perform the evaluation considering the eliminatory scenarios.

A simpler framework is sought in which managers would be able to see all the options in the decision-making moment and have more possible insights. For instance, they should understand the difference in the results between the feasible and the non-feasible scenarios. Thus, the option made was to allow MCDM to perform the prioritization, including defining the elimination criterion.

To this end, for evaluation purposes, indicators *I2*, *I3,* and *I4* were addressed by domain experts in defining their weightings. In this specific case, all indicators were evaluated as having the same importance by all domain experts. Indicator *I1b* should be higher than the sum of the other three indicators. This weighting occurs, because indicator *I1b* has an eliminatory role among the scenarios with the role of selecting only the feasible scenarios for the process, as explained in Section 4.4. Weightings are expressed in Table 9.

Table 9
Indicator weights.

I1b	*I2*	*I3*	*I4*
0.52	0.16	0.16	0.16

With the values obtained in the simulation stage and with the weightings established in the previous procedure, a ranking process can be performed to find the best alternative among the scenarios evaluated. Therefore, given this complex decision space with several indicators and several scenarios, using multicriteria methods to support the decision (MCDM) becomes essential in achieving a statically significant choice.

To apply an MCDM, the first step is selecting the optimal method for the case. Several methods exist with different focuses, from aiming at a qualitative analysis or causal relationships among the criteria to selecting preferences and ranking of alternatives. In this sense, some model-related considerations must be observed for a better selection:

1. Indicators have different objectives: *I4* and *I1b* should be maximized, while *I3* and *I2* should be minimized;
2. Indicators do not have the same scales: *I1b* is binary, *I4* is fractional, and *I2* and *I3* are continuous;
3. Indicators have different weightings from each other;
4. A scenario must be chosen from among the options.

Therefore, with support from [17] and the authors' preferences, the method chosen was PROMETHEE II. This method enables performing the comparison and ranking of different scenarios, which is fundamental for this case. To this end, the PROMETHEE II method, according to [68], results in a scenario listing based on how preferable a given scenario is. Therefore, PROMETHEE II is applied according to the objectives of the indicators, as mentioned above. The method is divided into four steps. For the calculation of the first step, the array is first normalized and, if the goal is maximizing, Equation 7 is used.

$$x'_{ij} = (xij - \min(xij))/(\max(xij) - \min(xij)) \quad \forall\, i \,\forall\, j \tag{7}$$

Otherwise, Equation 8 is used, generating Table 10.

$$x'_{ij} = (\max(xij) - xij)/(\max(xij) - \min(xij)) \quad \forall\, i \,\forall\, j \tag{8}$$

Table 10
Normalized input values.

C_i	I1b	I2	I3	I4
C_1	1	0,93911	0,97939	0,33491
C_2	1	0,97775	0,99712	0,80509
C_3	1	1,00000	1,00000	1,00000
C_4	0	0,61834	0,64414	0,02815
C_5	0	0,92286	0,93957	0,11999
C_6	1	0,99343	0,99313	0,63413

C_7	0	0,00000	0,00000	0,53056
C_8	0	0,35258	0,34589	0,22857
C_9	0	0,72398	0,71318	0,00000

Then, the criteria preference matrix is calculated by means of Equation 9.

$$P\left(x'_{ij}, x'_{kj}\right) = P_j\left(u_j(x'_i) - u_j(x'_k)\right) = P_j(\delta_{ik}\ )\ \ \forall\, j \tag{9}$$

In case $P_j(\delta_{ik}\ ) < 0$, it receives the value 0. The result of this calculation can be seen at Tables 11-14

Table 11
Preference matrix relative to criterion I1b

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.00	0.00	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_2	0.16	0.00	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_3	0.16	0.16	0.00	0.16	0.16	0.16	0.16	0.16	0.16
C_4	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.16	0.00
C_5	0.00	0.00	0.00	0.16	0.00	0.00	0.16	0.16	0.16
C_6	0.16	0.16	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C_8	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00
C_9	0.00	0.00	0.00	0.16	0.00	0.00	0.16	0.16	0.00

Table 12
Preference matrix relative to criterion I2

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.00	0.00	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_2	0.16	0.00	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_3	0.16	0.16	0.00	0.16	0.16	0.16	0.16	0.16	0.16
C_4	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.16	0.00
C_5	0.00	0.00	0.00	0.16	0.00	0.00	0.16	0.16	0.16
C_6	0.16	0.16	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C_8	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00
C_9	0.00	0.00	0.00	0.16	0.00	0.00	0.16	0.16	0.00

Table 13
Preference matrix relative to criterion I3

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.00	0.00	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_2	0.16	0.00	0.00	0.16	0.16	0.16	0.16	0.16	0.16
C_3	0.16	0.16	0.00	0.16	0.16	0.16	0.16	0.16	0.16
C_4	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.16	0.00
C_5	0.00	0.00	0.00	0.16	0.00	0.00	0.16	0.16	0.16
C_6	0.16	0.00	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
C_8	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.00	0.00
C_9	0.00	0.00	0.00	0.16	0.00	0.00	0.16	0.16	0.00

Table 14
Preference matrix relative to criterion I4

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.00	0.00	0.00	0.16	0.16	0.00	0.00	0.16	0.16
C_2	0.16	0.00	0.00	0.16	0.16	0.16	0.16	0.16	0.16
C_3	0.16	0.16	0.00	0.16	0.16	0.16	0.16	0.16	0.16
C_4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16
C_5	0.00	0.00	0.00	0.16	0.00	0.00	0.00	0.00	0.16
C_6	0.16	0.00	0.00	0.16	0.16	0.00	0.16	0.16	0.16
C_7	0.16	0.00	0.00	0.16	0.16	0.00	0.00	0.16	0.16
C_8	0.00	0.00	0.00	0.16	0.16	0.00	0.00	0.00	0.16
C_9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

In the second step, the preference matrices (Tables 11-14) are aggregated considering their weightings w_j, through Equation 10.

$$\pi(\delta_{ik}\ ) = \ \left(\sum_{j=1}^{k} w_j P_j(\delta_{ik}\ )\right) / \sum_{j=1}^{k} w_j \tag{10}$$

The result is shown in Table 15.

Table 15
Aggregate matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
C_1	0.00	0.00	0.00	0.25	0.25	0.00	0.21	0.25	0.25
C_2	0.12	0.00	0.00	0.25	0.25	0.08	0.25	0.25	0.25
C_3	0.12	0.12	0.00	0.25	0.25	0.12	0.25	0.25	0.25
C_4	0.00	0.00	0.00	0.00	0.00	0.00	0.08	0.08	0.04
C_5	0.00	0.00	0.00	0.12	0.00	0.00	0.08	0.08	0.12
C_6	0.12	0.04	0.00	0.25	0.25	0.00	0.25	0.25	0.25
C_7	0.04	0.00	0.00	0.04	0.04	0.00	0.00	0.04	0.04
C_8	0.00	0.00	0.00	0.04	0.04	0.00	0.08	0.00	0.04
C_9	0.00	0.00	0.00	0.08	0.00	0.00	0.08	0.08	0.00

The third part refers to the representation of the overcoming flows ϕ. The first value is the positive flow, or input, calculated by Equation 11, which represents the intensity of preference of a scenario over all others.

$$\phi_i^+ = \sum_{i=1}^{k} \pi(\delta_{ij}) \; \forall\, i \tag{11}$$

The second value is the output or negative flow. This represents the preferred intensity of all scenarios over any given one, which is calculated by Equation 12.

$$\phi_j^- = \sum_{j=1}^{k} \pi(\delta_{ij}) \; \forall\, j \tag{12}$$

Finally, the fourth part performs obtaining general scenario alternatives. For this purpose, the net flow is used, i.e., the balance between the values calculated in the third part is the result of the Equation 13.

$$\phi_i = \phi_i^+ - \phi_i^- \quad \forall\, i \tag{13}$$

The results are displayed in Table 16. With this result, a view of the best improvement proposal to be implemented can already be had, as shown in Fig. 13.

Table 16
Scenarios with input, output and net flows.

	$\boldsymbol{\phi_i^+}$	$\boldsymbol{\phi_i^-}$	$\boldsymbol{\phi_i}$
$\boldsymbol{C_1}$	1.21	0.40	0.81
$\boldsymbol{C_2}$	1.45	0.16	1.29
$\boldsymbol{C_3}$	1.61	0.00	1.61
$\boldsymbol{C_4}$	0.20	1.28	-1.08
$\boldsymbol{C_5}$	0.40	1.08	-0.68
$\boldsymbol{C_6}$	1.41	0.20	1.21
$\boldsymbol{C_7}$	0.20	1.28	-1.08
$\boldsymbol{C_8}$	0.20	1.28	-1.08
$\boldsymbol{C_9}$	0.24	1.24	-1.00

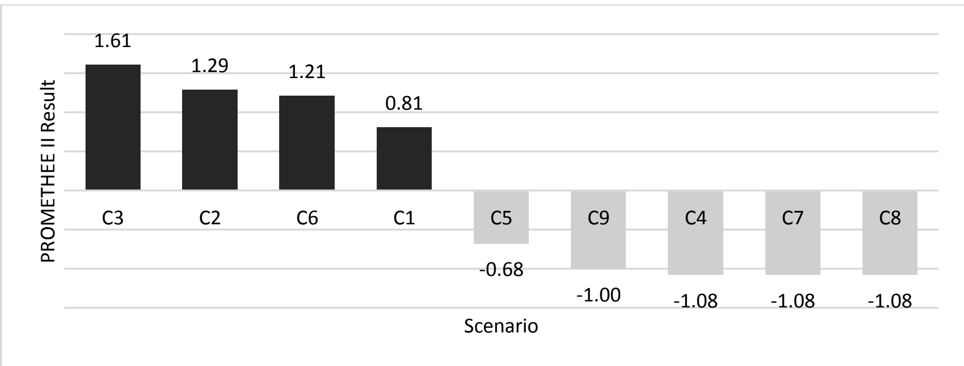


Fig. 13. PROMETHEE II Result.

Thus, when evaluating the objective results with MCDM, the four scenarios that presented positive net flow and the four with negative net flow can be highlighted. The four scenarios that presented positive values are those that meet the criterion of greatest impact (*I1b*), which represents the bed occupancy rate being between 0.75 and 0.95. Among these four scenarios, C_2 and C_3 are in the best positions and point to keeping the number of beds at 30 and reducing, respectively, the time of the etiological assessment to 10.631 and 7.200 minutes.

To understand whether this solution is still the best under other hospital conditions, i.e., where some criteria are more important than others, a sensitivity analysis of the criteria weightings was provided. This analysis was performed by exploring an increase of 10, 20 and 50% in one criterion weighting with the other criteria maintaining their original weightings. This was repeated for each criterion. The result observed is that the ranking of scenarios was always the same. This, therefore, emphasizes that efforts to improve this process should be directed to this activity because it is the best choice even under other hospital conditions.

5. Results and discussion

This paper's contribution is presenting a combination of PM, MCDM and DES to generate process improvements in the healthcare area enabling a systematization and formalization regarding the combination of these three techniques in a single process improvement framework. Thus, the combination of PM and DES will develop process simulation in an agile manner and in a common language with process specialists. Additionally, the combination of DES and MCDM will contribute to creating a robust decision-making process of process improvement, which addresses numerous scenarios with several indicators, and thus avoid endangering patients' lives by not requiring on-site testing.

To validate the proposal, this combination was applied to the stroke care and treatment process, which is extremely important, given that stroke is the second leading cause of death in the world and any improvement in this process has a high impact on patient health. As shown by the case study, the indication for reduction of the time of etiological assessment is indicated as the best path to follow so that the process reaches better values in its strategic indicators. However, it is worth mentioning that, despite this case study indicating a specific recommendation for point for improvement and how the recommendation should be applied, i.e., by reducing the duration of the etiological assessment activity, the simulation is limited by the granularity used, i.e., activities and resources. Therefore, given that etiological assessment is a complex activity that might have sub-activities, specific equipment, and so on, that may require an analysis of this activity to understand how this improvement should be undertaken. In this case, one future work possibility is reapplying this framework specifically in the etiological assessment activity to observe its behavior.

The authors understand that this methodology proposal can promote robustness in complex and sensitive scenario management processes through an efficient way to develop improvements to the process by applying the methodology from the beginning to the end. Additionally, such a framework is also perceived as having potential for several other uses, either in more in-depth study focused on the etiological assessment stage with a view to achieving the improvement targeted or in establishing digital and operational versions of the monitoring and risk management process. For instance, in the initial periods of the COVID-19 pandemic, this methodology could have been applied to define the best scenarios for bed distribution within hospitals.

Thus, several points have been raised in developing this paper. First, due to the easy communication enabled by PM during the development of the operational model, a time slot that is disregarded as part of the process was discovered. This is the time required for cleaning and sanitizing of beds, which takes between 1 and 4 hours immediately following the patient's discharge, and which can represent a significant time and potential for improvement in such a time sensitive process. Also, the combination of

DES methods with probability distributions obtained with PM made it possible to establish an operational model statistically similar to reality. With this operational model, experiments could be performed in several scenarios that were later evaluated using the main management indicators that measure this process. The decision-makers pointed out that this framework will be useful in applying improvements in the process. They said that this framework proved their suspicion that etiological assessment was the activity that should be improved. The nurses also pointed out that, with this framework, they will be able to have arguments with managers and stakeholders with better basis when requesting a specific process improvement or modification. Due to the COVID-19 situation in the hospitals, this improvement has not yet been applied. However, the hospital where this case study was applied has a research group for the stroke process and, as soon as possible, the suggestions will be implemented. With this, the proposal presented a robust, assertive, and safe way to bring improvements to sensitive and complex processes.

In the literature, the growth of investigation on the three techniques used for process improvements in the healthcare area is remarkable. Authors [29, 34, 35, 37] develop their research addressing as main technique the use of MP complemented by several other techniques to bring improvements to healthcare delivery processes. [26, 34–41] present work using the combination of PM, mainly with a focus on data exploration, and DES for the simulation of alternative improvements. From another perspective, [54, 55] apply in the same context the combination of DES to simulate scenarios and MCDM to robustly evaluate the indicators extracted. Therefore, from the above-mentioned studies, even with several studies in the area over the last few years, no author has explored the combination of these three techniques. Thus, this paper is the first to expand this frontier of knowledge and to explore this robust combination of MP, DES, and MCDM in the healthcare services area.

From another perspective, barriers and challenges have also stood out throughout this development. First, it is essential to point out that, in general, hospital and healthcare environments are not mature enough to receive process improvement initiatives that depend on data. Therefore, as the case studied, it is common for healthcare environments not to have digital records of all events in their processes and to store only data useful to feed key process indicators. This impairs the process of creating an operational model. Additionally, the framework developed is only capable of pointing out what is visible in the granularity of the simulation performed and, therefore, only capable of indicating the specific point of the process to which experts should direct their efforts and root cause studies in order to achieve the improvements with the highest impact.

Therefore, there is still a lot of work to be done. First, an entire series of studies using this same case can be performed, either in investigating the root cause for the point of improvement established through this proposal and in developing a framework extension with root cause analysis, or even in performing a new iteration of the framework within a subprocess, for instance, during etiological assessment to go more in-depth in the exact point to be improved and validate the proposal replicability in different granularities. Also, applying this technique on other fronts of the healthcare area to validate the proposal is of interest, for instance, in the urgency and emergency department of a hospital or in oncology care. As the framework pools three techniques, studying the automation of this logical flow of data and process mining is worthwhile until decision support can be delivered in a single system aiming at a simpler execution of the entire process.

6. Conclusion

In this paper, a framework was proposed that combines the techniques of process mining (PM), discrete event simulation (DES), and multicriteria methods to support decision-making (MCDM) in order to bring improvements to healthcare processes. An application has been conducted in the clinical path for dealing with the stroke treatment process. Thus, from the development of such a combination, through the use of PM to study event records and serve as the bridge for communicating modeling to experts, DES to digitally recreate the process and MCDM PROMETHEE II to select the improvement that the process should strive for, it was possible to prove that this proposal is capable of collaboration to improve complex and sensitive processes in a robust way and still able to have a clear communication with stakeholders of the process.

However, the framework developed was evaluated only in one hospital and, therefore, still requires further studies to understand the limitations of the proposal as well as other possible uses. To this end, a thorough analysis of the etiological assessment stage, with or without the re-use of this framework to achieve the process improvement, can be performed. Also, the replication of this proposal in another environment must be undertaken to evaluate the replicability of the framework, or even in developing the integration of these techniques for systematization and faster and more simplified deployment of the proposal.

CRediT Author Statement

Pedro Antonio Boareto: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – Original Draft, Visualization. **Juliana Safanelli:** Validation, Investigation. **Rafaela B. Liberato:** Validation, Investigation. **Carla H C Moro:** Validation. **José Eduardo Pécora Junior:** Conceptualization, Writing - Review & Editing. **Claudia Moro**: Validation. **Eduardo de Freitas Rocha Loures:** Conceptualization, Writing - Review & Editing. **Eduardo Alves Portela Santos:** Conceptualization, Methodology, Writing - Review & Editing, Supervision.

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