Optimizing the Emergency Room Visit Times for Patients With Sepsis by Applying Process Mining and Automation

Final Report

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Executive Summary

This report is focused on examining the existing processes performed in emergency departments for incoming patients with sepsis and proposing a solution to optimize their wait times. The importance of the defined problem is explained by sepsis' global reach, fast disease progression and high mortality rates. To help combat such a life-threatening condition, the proposed solution is to utilize process mining and automation in the context of processes in the emergency rooms required for sepsis' diagnosis and the following treatment. With gathering data of the current state, analyzing it and revealing bottlenecks and inefficiencies, there is a potential to apply automation and improve the whole algorithm of sepsis patients' treatment from admission to the emergency room till their discharge. As a result, there is an expected increase in efficiency of the way emergency departments operate, but more importantly, a possibility to save millions of lives.

Introduction

The advancement in technology and digital adoption is impacting every industry. Though there are disadvantages of increasing dependence on technology, if used in the right way, it could have enormous positive and revolutionary impact. Our client Bayer, is on a mission to capitalize on the opportunities that are arising as a result of digitalization, especially in the health care sector (Bayer, n.d.-a). One particular opportunity of digitalization we found is in optimizing the emergency room visit times for patients with sepsis by applying hyper automation.

Our focus is on improving the visit times in an emergency room for sepsis since 1 of 5 deaths globally are due to sepsis and there were more than 50 million active cases as of 2017 (Wang et al., 2017). Hyperautonmation is the combination of automation approaches with the data science approach during the execution of a process to reach the optimal process flow (Bayer, n.d.-b). Process mining can be used on the data gathered from the emergency rooms on patients with sepsis to compare the as-is process to the ideal process. Based on the results, automotive technologies can be used to optimize the admission to discharge process in an emergency room for incoming patients with sepsis to timely provide treatment.

This report explains the problem in detail followed by the need to solve the problem. It then describes the conceptual solution by describing the business, data and technology architecture required. The report also includes an implementation plan, particularly the next steps and risk and mitigation plan.

Problem Definition

Sepsis is a potentially life-threatening condition following the body's response to infection which causes inflammation and can lead to tissue injury or organ dysfunction (World Health Organization, n.d.). There are three main stages associated with the progression of this condition: sepsis, severe sepsis and septic shock. During the first stage, an individual might have confirmed or suspected infection and experiences systemic inflammatory response syndrome which can be defined by meeting at least two of the following criteria:

- Body temperature to be over 38 or under 36 degrees Celsius,
- Heart rate to be greater than 90 beats per minute,
- Respiratory rate to be greater than 20 breaths per minute or partial pressure of carbon dioxide less than 32mmHg,
- Leukocytes count to be greater than 12000 or less than 4000 microliters or over 10% immature forms or bands (Chakraborty & Burns, 2023).

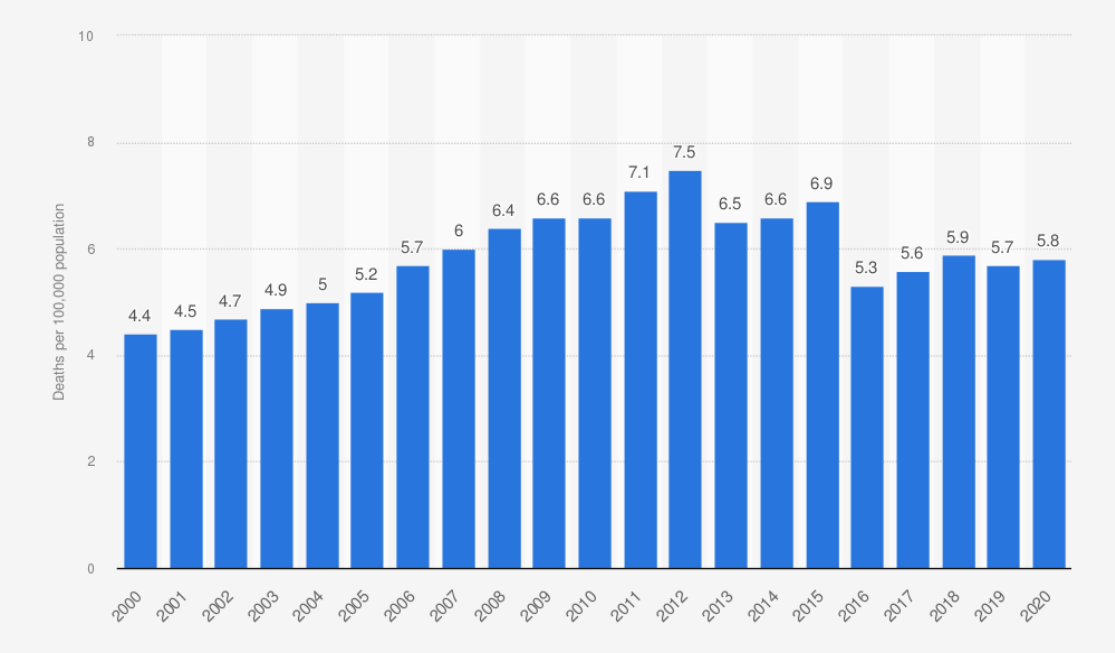
Next, severe sepsis is recognized when there is sepsis and signs of end organ damage and septic shock is defined by persistent hypotension despite adequate fluid resuscitation to exclude the possibility of volume depletion as a cause of hypotension (Mahapatra & Heffner, 2023). It can take as little as 12 to 24 hours for an initial infection to develop sepsis and progress to septic shock, which has mortality rate estimates ranging from 30% to 50% (Ryding, 2018; Zimlich, 2022).

Given that such conditions can get worse that fast, the need to get admitted into the emergency room and receive treatment as soon as possible is imperative. However, in 2021, 90% of the time Canadians' emergency department visit from admission to completion was within 40.7 hours (Woo, 2022). There is a clear disparity between how much time is needed and how much is available to receive treatment in time. So, the problem we are trying to address is the process of incoming patients with sepsis being admitted to an emergency room till their discharge. There is a need to optimize this process due a variety of reasons; However the two major ones we have outlined are:

- **Severity of the disease:** In 2017, there were approximately 50 million active cases of sepsis and 11 million global deaths due to sepsis, accounting for 20% of the global deaths (Wang et al., 2017). The US Emergency identified millions of visits to emergency rooms in suspicion of sepsis on an annual basis (Wang et al., 2017). Research has also identified sepsis to be the leading cause of in-hospital deaths in the United States costing people and the government more than 24 billion dollars annually (Rudd et al., 2020). Even in Canada, sepsis has been a constant cause of death. In 2020, 6 out of 100,000 people died due to sepsis (Figure 1).

Figure 1

Death Rate For Sepsis in Canada From 2000 to 2020 (per 100,000 Population)

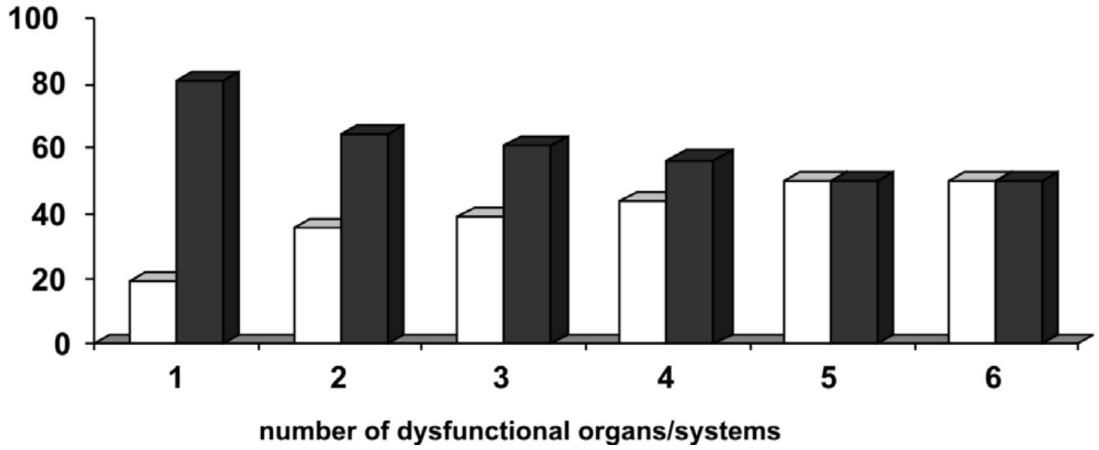


Note. From Death rate for sepsis in Canada from 2000 to 2020 (per 100,000 population), by StatCan, 2022, *Statista*, (https://www.statista.com/statistics/434391/death-rate-for-sepsis-in-canada/). In the public domain.

- **Management of sepsis**
  Given that sepsis is a life threatening disease, it is important to recognize the disease and provide the treatment in the right hour. As per the research article, Management of Sepsis, for emergency physicians the main challenge is the management of septic patients and most often that not, the first medical point of contact are the physicians in the emergency room for patients with sepsis (Gavelli et al., 2021). Hence, the physicians in the emergency rooms play an important role in the treatment of the disease.

Figure 2

Distribution of Patients With Sepsis Whose Sepsis Was Diagnosed and Whose Was Not



Note. White columns: percentage of patients with sepsis diagnosis; black columns: percentage of patients without diagnosis. Chi-square test (p=0,006). From "Epidemiology of severe sepsis in the emergency department and difficulties in the initial assistance", by E. Rezende, J. M. Silva Jr., A. M. Isola, E. V. Campos, C. P. Amendola, and S. L. Almeida, 2022, *Clinics (São Paulo, Brazil), 63*(4), 457–464 (https://doi.org/10.1590/s1807-59322008000400008).

Based on the research by Rezende et al. (2008), there are higher chances of physicians in emergency rooms not diagnosing patients with sepsis. Since, the physicians in emergency rooms are important members for the treatment in the early stages of the disease, it is important for the hospitals and medical industry to improve and optimize the treatment process of patients with sepsis in emergency rooms in order to reduce deaths due to sepsis and improve resource allocation within the hospital.

The scope of the project is to improve proficiency at present, but the World Health Organization has stated limitations on assessing and collecting data on sepsis globally. Reasons for such limitations majorly include lack of access or availability of databases that store patients' records. Therefore, most of the global data on sepsis is from 2017 as that was the most recent scientific estimation on sepsis globally (World Health Organization, 2020). However, there is recent data on sepsis available for certain individual countries.

Even though sepsis is a worldwide issue, we have tried to look into the problem in Canada as the wait times in the emergency rooms vary and the way healthcare operates, in general, differs from country to country. What remains constant though, is Bayer's values for leadership, integrity, flexibility and efficiency (Bayer Global, n.d.). Our solution will be aimed to optimize the wait time in an emergency room by applying process mining and automation which resonates with one of Bayer Canada's business processes, radiology, which is committed to "developing products, tools and services all aimed at increasing diagnostic confidence and operational efficiency" (Bayer Canada, n.d.). Moreover, Bayer is not new to process mining as there are use

cases of applying it for audit or supply chain and procurement, by utilizing Celonis, which is a market leader in process mining software (Detwiler, 2022).

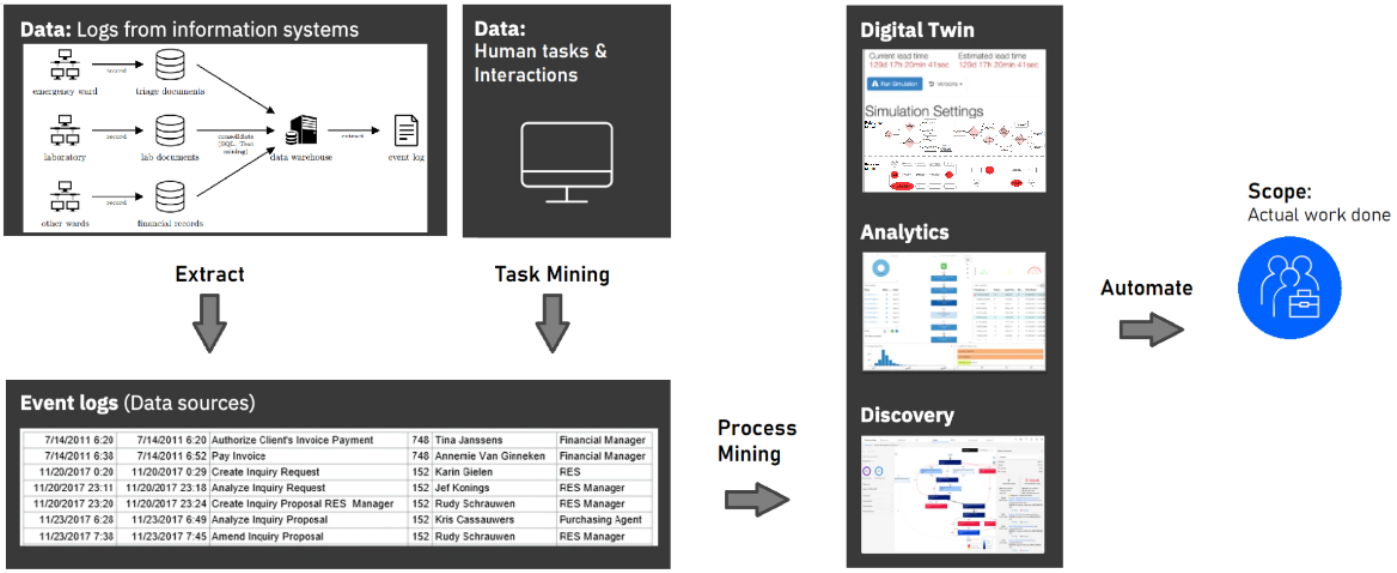
Conceptual Solution

Process Mining

Process mining is an advanced data-driven technique that enables organizations to gain valuable insights into their business processes by analyzing event data generated when performing tasks (van der Aalst, 2011). This approach involves extracting information from event logs to discover, monitor, and optimize processes, and combines it with task mining, which captures human interactions within business processes (van der Aalst, 2012; Davis, 2021). The steps to optimize business operations with process mining involves creating a digital twin for simulation, using analytics for insights, discovering actual process flows, and determining the scope to prioritize areas that benefit the most from automation (Davis, 2021). Although process mining is a mature analysis method, it has gained significant traction in various industries like healthcare, offering a powerful tool for organizations to better understand and optimize their operations (Tiwari et al., 2008). From Figure 4 on the Steps of Process Mining, we can see the overall process that would be applied to general industries.

Figure 4

Steps of Process Mining



Note: Adapted from "The Art of Automation: Chapter 11 — Automation and Process Mining" by Harley Davis, 2021, IBM (https://www.ibm.com/cloud/blog/art-of-automation-chapter-11).

Application of Process Mining *to ER*

When looking at the issue of sepsis illness and death during patient treatment in emergencies, we look to decrease the loss of life from sepsis by using process mining to assist in the key issues of sepsis stated earlier:

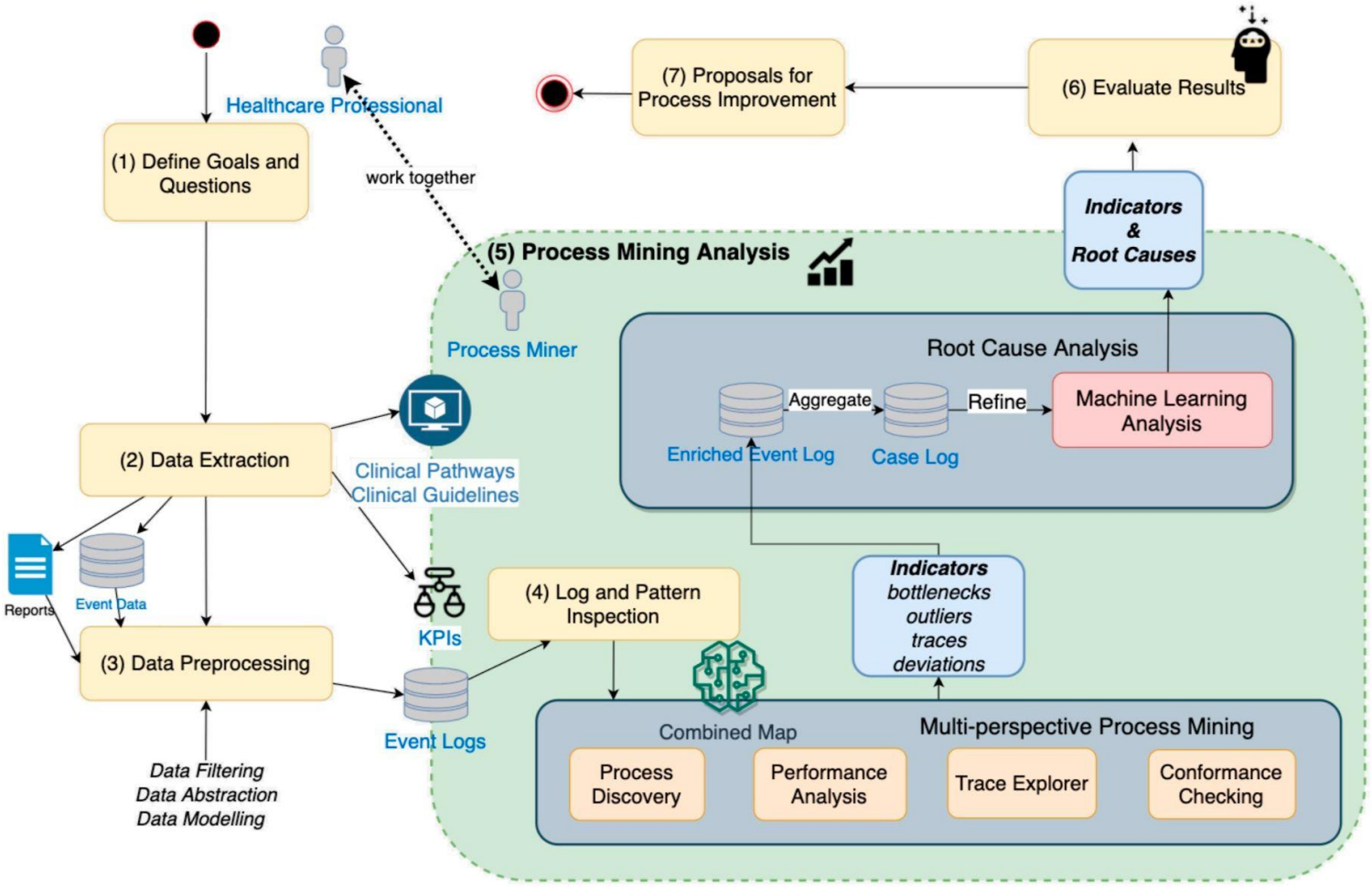
1. **Rapid progression of sepsis and high mortality rates:** It can take as little as 12 to 24 hours for an initial infection to develop into severe sepsis and septic shock, which has mortality rate estimates ranging from 30% to 50% and resulting in 11 million deaths worldwide.
2. **Time-sensitive nature of sepsis:** Given that sepsis is a life-threatening condition, it is important to recognize and treat it as soon as possible. However, in 2021, 90% of the time Canadians' emergency department visit from admission to completion was within 40.7 hours.
3. **Frequency, cost, and identification difficulty of sepsis in hospitals:** Research has identified that there are higher chances of physicians in emergency rooms not diagnosing patients with sepsis, costing $24 billion annually to deal with the illness. Furthermore, ER physicians are the first medical contact for sepsis patients

In healthcare, process mining has demonstrated significant value in optimizing clinical processes, resource allocation, and hospital workflows by identifying bottlenecks, inefficiencies, and deviations from best practices (Swennen et al., 2019; Mans et al., 2015). As a result, process mining can contribute to improved patient outcomes, reduced waiting times, and enhanced resource utilization (Mans et al., 2015). The application of process mining in healthcare also uncovers historical patterns in processes, highlighting its potential for optimizing sepsis treatment in hospitals (Rojas et al., 2016). For sepsis patients in emergency rooms, process mining begins with defining the goals and questions. It then involves data extraction from various sources, followed by data preprocessing to ensure accurate and consistent data for analysis (van der Aalst et al., 2012). The next steps include log and pattern inspection, as well as process discovery to create process and reference models, which are then compared to identify improvements.

Process mining analysis involves multi-perspective process mining, healthcare professionals and process miners working together to focus on indicators, root cause analysis, and machine learning analysis to identify indicators and root causes of inefficiencies (Mans et al., 2015). By comparing actual processes to best practices from organizations like the Surviving Sepsis Campaign, deviations can be addressed, ultimately improving patient outcomes and resource utilization (Critical Care Medicine, 2021). Specialized software for simulations helps refine the overall process, addressing sepsis issues such as rapid progression, high mortality rates, and difficulty in diagnosis (van der Aalst et al., 2012). The process concludes with the evaluation of results and proposals for process improvement. In summary, the application of process mining in emergency rooms enhances patient care by targeting critical aspects of sepsis treatment, resulting in more efficient and effective care for patients. The potential application of process mining for sepsis treatment in emergency rooms will be explored in the sections of business architecture, data architecture, and technology architecture.

Figure 5

Process Mining Solution in ER in Hospitals



Note. This diagram maps out the important steps for the solution of process mining applied to Sepsis in a hospital. From "Multi-perspective process mining for emergency process" by Erdogan TG and Tarhan AK, Health Informatics Journal, 2022. (https://journals.sagepub.com/doi/full/10.1177/14604582221077195)

Business Architecture

Patient Flow Management

One key business process execution that would be significantly impacted if process mining were applied is patient flow management, as activities are modified and resorted, patients would be moved around differently through the ER process. Some patient pathways in sepsis management

are too formulaic and straightforward, which is illogical because of the immediate treatment that sepsis demands.

A real-life case called the “Superfluid Hospital Project”, which was conducted at Braunschweig Hospital in Germany by Dr. Goepfert, attempted to improve the patient’s care and hopsital’s resource allocation through process mining (Martin et al., 2022). Their focus was on cardiology patients, which is another sector of illnesses like Sepsis which require timely and efficient management in emergency rooms. Using their IT systems originating from radiology, the Lab, hospital IT systems, and so forth, they generated event logs and used Celonis in conjunction to map all the activities in the ER room for patients. As a result, they conceptually reduced the amount of activities in the process by 47% and unnecessary connections between activities by 60%, resulting in a model for a much smoother and timely ER process for patients in desperate need of cardiology services.

Through this case, it is clear that process mining being applied to Sepsis will strongly impact regular business functions in an ER room, as activities will be eliminated, adjusted, or created in the pursuit of reducing the amount of time needed for Sepsis patients to move through emergency rooms. As an added benefit, this will allow less resources to be pushed towards. If possible, integrating process mining functionalities into existing hospital IT systems would allow healthcare professionals to continuously adjust their processes to afford to give the best care for patients in the needed time required.

Resource Allocation

The use of medical resources, staff, equipment, and medication in the hospital will be severely shifted through the application of the recommendations made from process mining. This would lead to significant cost savings, since Sepsis patients where $24 billion is spent globally, and save hospitals greater financial resources to put towards other uses. When looking at financial and operational key performance indicators to review the financial and operational effects of processes through the ER room, opportunities to reduce unnecessary actions could further reduce the time for treating sepsis patients (Martin et al., 2022).

Conformance and Guidelines

Conforming to strict sepsis guidelines will also need to be reviewed, as hospitals globally diverge from reference models produced by organizations like the Society of Critical Care Medicine and European Society of Intensive Care Medicine (2021). One study by Mannhardt and Blinde (2017) on a Dutch hospital noticed that divergence from general sepsis guidelines resulted in strong time differences between admission and application of antibiotics, which is stated that it should be less than 1 hour (Critical Care Medicine, 2021). Furthermore, lactic acid should be measured less than 3 hours from the moment a patient enters the emergency room with the possibility of sepsis. However, it was seen that 58.5% of patients are not treated with antibiotics within 1 hour if they are possible sepsis carriers, which is a very strong deviance from general guidelines. However, only 0.7% of patients did not have their lactic acid measured within 3 hours (Mannhardt et al., 2017).

From this research, proper sepsis treatment must be applied for the sake of the patient. Thus, process mining would allow emergency room processes to conform better with guidelines set by professional medical organizations to maximize patient care and minimize hospital resources.

Transforming Current Healthcare IT Systems

Although there are many opportunities for process mining to benefit in healthcare, the application of process mining in hospitals is difficult and not as accurate as it could be do to low quality data, impreciseness, and the vast amount of processes needed not only for sepsis but other illnesses that share many of the same processes (Martin et al., 2022). Thus, numerous steps in the hospital should be applied after process mining has occurred to ensure continual efficiency benefits. This includes "integrat[ing] process mining functionalities into existing systems" as stated by Martin et al. (2022). Although process mining is inexpensive and can be simulated multiple times, the task of communicating with healthcare professionals, extracting and minimizing the massive data from hospitals, and other burdens that come from the steps in process mining, healthcare systems should adopt process mining functionalities, like automatic event log creation, to allow ease of updating ER processes. Furthermore, healthcare professionals should have tools that allow them to implement these changes themselves rather than having an extreme dependance on process mining engineers and experts so changes can be made fast and inexpensively. Finally, process mining should be applied to time-urgent conditions like Sepsis to not only benefit the patient but the financial well-being of the hospital.

Data Architecture

Two key data elements are needed to make this solution a success: 1. Event Logs generated through the data collections points for a Sepsis Patient and 2. The human activities done in the ER process are captured through task mining. After the data is compiled a process model and reference model is created and compared to discover discrepancies and bottlenecks that can be explored and improved.

Event Logs

To start the process, first it is necessary to understand where the data must come from to create the event logs. To create comprehensive event logs in an emergency department for a hospital, several data sources need to be considered and integrated (See Figure 5 on Hospital Event Log Origins). This process involves the following steps:

1. *Data collection from the emergency department:* Patient information, including demographics, symptoms, and vital signs, is recorded during the triage process (Mans et al., 2010). This information is typically documented within electronic health records (EHRs) and subsequently transferred to a centralized data warehouse for further analysis and storage (Raghupathi & Raghupathi, 2014).
2. *Data collection from laboratory systems:* Laboratory test results, such as blood tests, imaging studies, and microbiology cultures, are crucial for diagnosing and treating patients in the emergency department (Wang et al., 2018). These results are recorded in laboratory information systems (LIS) and then consolidated into the data warehouse alongside triage data (Yoon et al., 2016).
3. *Data collection from other hospital departments:* In addition to emergency department and laboratory data, information from other hospital departments, such as billing,

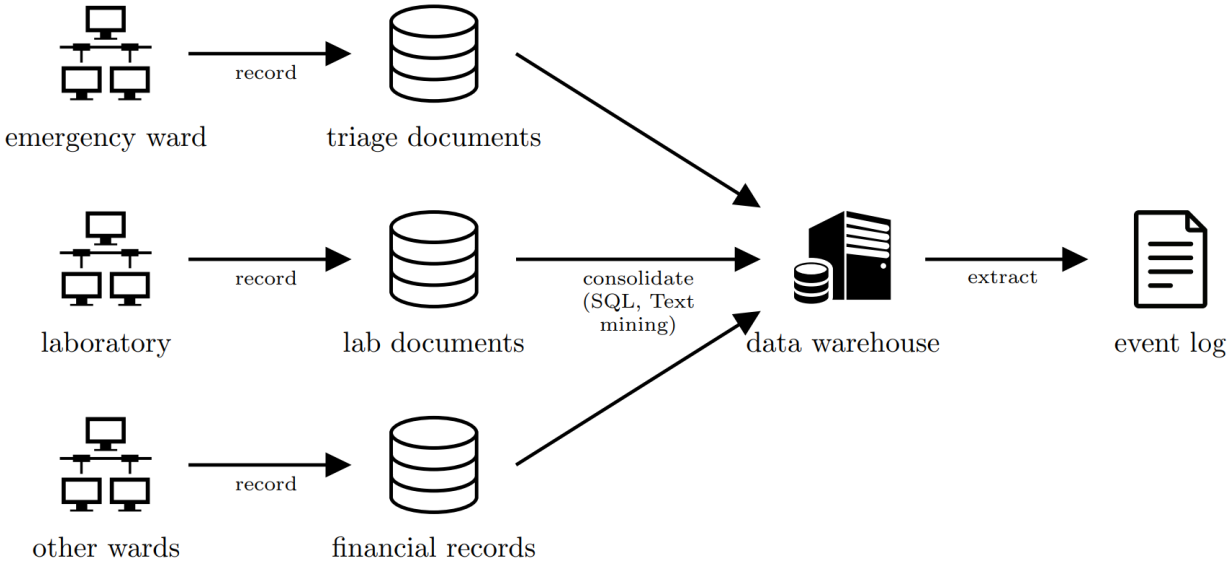
pharmacy, and inpatient wards, is essential for a comprehensive understanding of patient care and resource utilization (Hripcsak & Albers, 2013). This data is typically documented in various administrative and clinical systems, which are then integrated into the data warehouse (Weiskopf & Weng, 2013).

4. *Extraction and consolidation of event logs:* Once data from multiple sources is collected and stored in the data warehouse, it can be extracted, transformed, and loaded (ETL) into a unified event log format for process mining analysis (van der Aalst, 2011). This step involves the extraction of relevant data elements, such as timestamps, activity labels, and case identifiers, and the integration of these elements into a structured event log that captures the chronological sequence of events in the patient care process (Partington et al., 2015).

By following these steps, hospitals can create comprehensive event logs that provide valuable insights into the patient care process in the emergency department, enabling the identification of bottlenecks, inefficiencies, and potential areas for improvement (Swennen et al., 2019).

Figure 6

Hospital Event Log Origins



Note. This diagram maps out where the origins of event logs are in emergency rooms. From Analyzing the trajectories of patients with sepsis using process mining by Mannhardt, Felix & Blinde, Daan., 2017, Eindhoven University of Technology. (https://ceur-ws.org/Vol-1859/bpmds-08-paper.pdf)

Task Mining

In a hospital emergency room, the journey of a sepsis patient from admission to discharge or death involves a complex series of human activities and interactions, which are crucial to examine during the task mining phase of process mining. Upon admission, the patient is assessed by a triage nurse, who assigns a priority level based on the severity of the patient's condition (Farrohknia et al., 2011). Subsequently, the patient undergoes a detailed examination by an

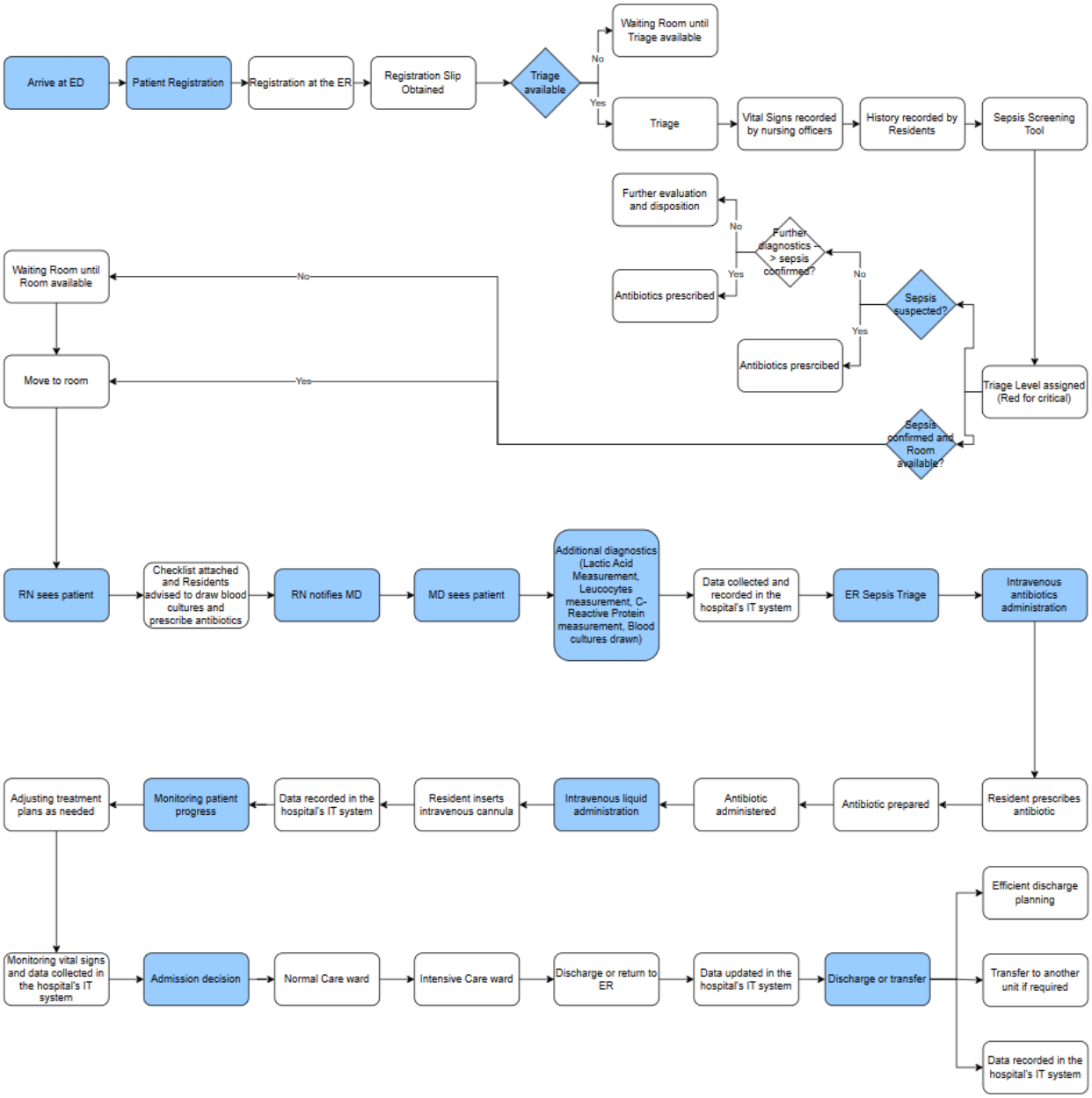
emergency physician, who orders relevant laboratory tests and imaging studies to confirm the diagnosis of sepsis (Seymour et al., 2017). These tests, performed by laboratory technicians, typically include blood cultures, complete blood count, coagulation studies, and lactate levels (Rhodes et al., 2017). Based on the results, the physician initiates appropriate antimicrobial therapy, fluid resuscitation, and supportive care, which are administered by the nursing staff (Rhodes et al., 2017). Throughout the treatment process, the patient's condition is continuously monitored, with vital signs and laboratory markers recorded in the electronic health record (EHR) (Weiskopf & Weng, 2013). In cases where sepsis progresses to severe sepsis or septic shock, the patient may be transferred to the intensive care unit (ICU) for further specialized care, including vasopressor administration and mechanical ventilation (Singer et al., 2016). Finally, the patient's outcome, either recovery and discharge or death, is documented in the EHR, along with any complications or interventions that occurred during their hospital stay (Yoon et al., 2016). See Figure 6 for a more comprehensive view of the task mining activities occurring through the Emergency Room Process. From this, it is combined with the IT event logs to create an enriched event log.

Abstract Process Model

Once the information from the event logs and task mining activities are combined, a process model is able to be completed. This congregates the activities found in each model into one process model, in which we have created a flow diagram based on our data findings. Combining IT and task mining data from various Emergency Room studies and process models, we created an abstract possible model for a sepsis patient seen in figure 7.

Figure 7

Abstract Process Model for Sepsis Patients in ER



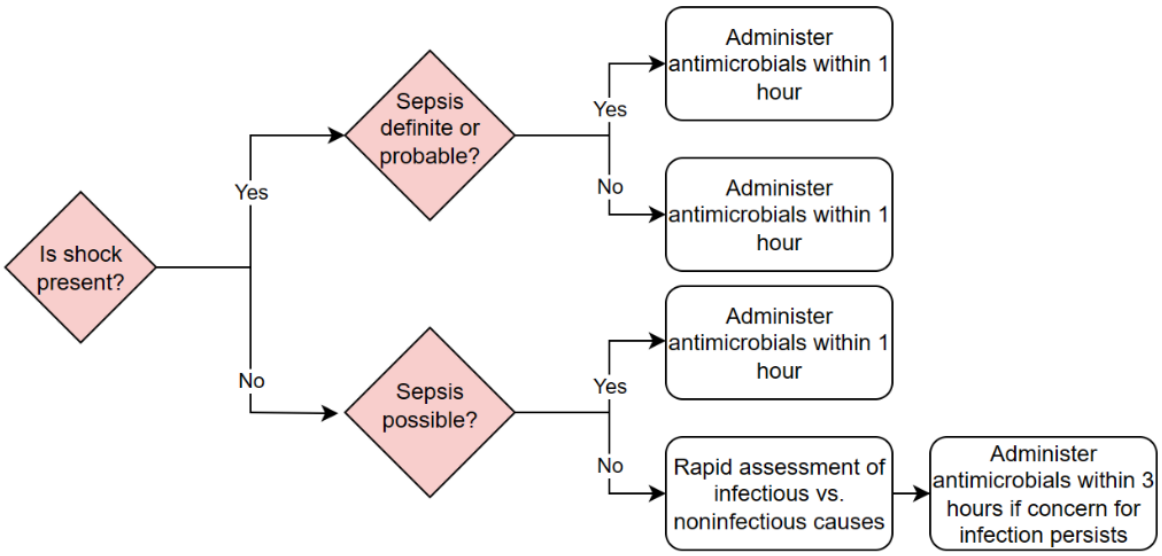
Note: This diagram shows an Abstract Process Model on the IT and task mining activities involved in an ER room for a sepsis patient. Items marked in blue are crucial activities involved in the ER room process. Information to create model by: Malhotra et al. (2022), Munoz-Game et al., (2022), Hitti et al. (2011), and Mannhardt et al., (2017) from the All India Institute Of Medical Science, Journal of Biomedical Informatics, Journal of Emergency Medicine, and Eindhoven University of Technology (See references).

Abstract Reference Model

After creating the process model, a reference model must be created as a standardized representation of the best practices and expected behavior within an industry (van der Aalst, 2011). By serving as a benchmark, it will allow a comparison between the actual processes in an emergency room against an ideal process model, which is used to identify deviations, inefficiencies, bottlenecks, and opportunities for improvement within current ER sepsis procedures (van der Aalst, 2011). Thus, we created a reference model using the information from general guidelines from the Society of Critical Care Medicine and European Society of Intensive Care Medicine (2021) in figure 8 and 9.

Figure 8

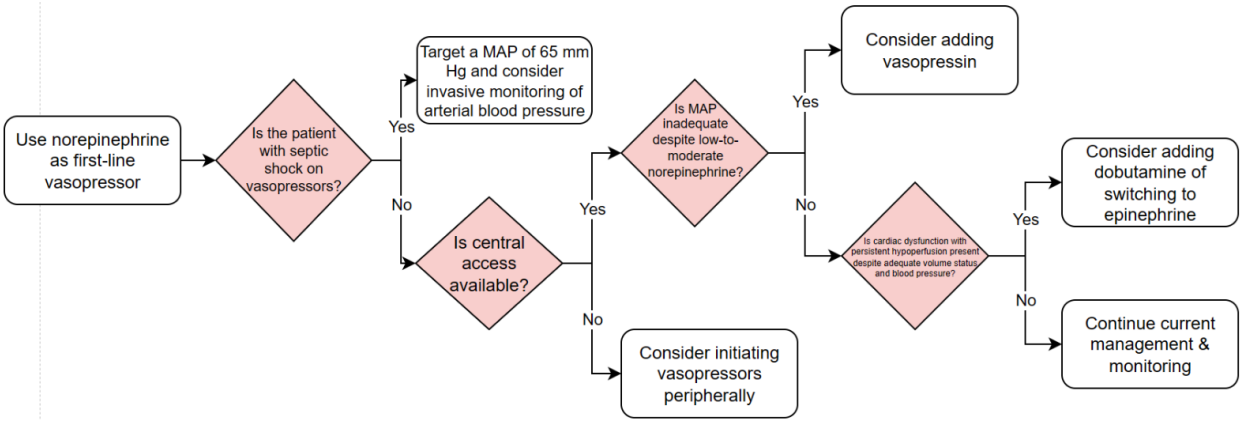
Abstract Reference Model for Antibiotic Timing (Sepsis Condition Unknown)



Note: Reference Model for treating sepsis patient in ER room when sepsis is possible or probable. Information to create model from "Surviving Sepsis Campaign: Antibiotic Timing" by Society of Critical Care Medicine and European Society of Intensive Care Medicine, 2021. (https://www.sccm.org/getattachment/14791d1a-4585-43d6-8a72-c81c786380fa/Surviving-Sepsis-Campaign-2021-Guidelines-Infographic_Anitbiotic-Timing.pdf?lang=en-US).

Figure 9

Abstract Reference Model for Vasoactive Management (Septic Shock)



Note: Reference Model for treating sepsis patient in ER room when patient enters septic shock. Information to create model from "Surviving Sepsis Campaign: Vasoactive Agent Management" by Society of Critical Care Medicine and European Society of Intensive Care Medicine, 2021 (https://www.sccm.org/getattachment/d981da2d-c6b2-4ced-af18-bfcbbf859499/Surviving-Sepsis-Campaign-2021-Guidelines-Infographic_Vasoactive-Agent.pdf?lang=en-US).

Comparison of Models

Once the Process Model (Figure 7) and Reference Model (Figure 8 and 9) for Sepsis Patients in ER are created, a comparison enables the identification of discrepancies and improvement opportunities (Rozinat & van der Aalst, 2008). Aligning these models helps pinpoint deviations from best practices, streamline workflows, and ultimately enhance patient outcomes and resource utilization (van der Aalst, 2016). Analyzing these models we created, some possible areas for improvement could include:

1. Triage process: Integrate the "Sepsis Screening Tool" from the process model into the reference models to ensure that patients are quickly and accurately identified as having sepsis.
2. Diagnostic integration: Incorporate Lactic Acid Measurement, Leucocytes measurement, C-Reactive Protein measurement, and Blood cultures.
3. Antibiotic administration: Align the reference models' antibiotic timing model with the process model to optimize the timing of antibiotic administration.
4. Waiting room management: Incorporate "Waiting Room until Triage available" and "Waiting Room until Room available" steps from the process model into the reference models.
5. Data collection and IT system integration: Integrate data collection, recording, and updating from the process model into the reference models.
6. Admission decision and ward allocation: Ensure that the reference models include a clear admission decision process and allocation of patients to the appropriate ward.

7. Efficient discharge planning: Incorporate efficient discharge planning from the process model into the reference models to ensure patients are discharged or transferred in a timely manner.
8. Vasopressor management: Include the vasoactive management model from the reference models into the process model to ensure that patients receive the appropriate vasopressor support.
9. Coordination: Improve communication between nursing officers, residents, and other healthcare providers in the process model to streamline patient management.
10. Resource availability: Ensure availability of resources such as blood culture bottles, antibiotics, and intravenous cannulas in the process model.
11. Staff training: Incorporate staff training in sepsis identification and management into the process model.

After identifying bottlenecks and discrepancies between the models, simulations must be run using specialized technology (See technology architecture) to generate valuable analytics and uncover insightful discoveries, which will eventually optimize and refine the overall process scope.

Technology Architecture

The admission to discharge process in an emergency room for arriving patients with sepsis can be greatly improved with the aid of process mining and automation technologies. The hospital also must deploy several technologies made efficient using Process Mining, as highlighted below, to optimise the process:

EHRs, or electronic health records, EHRs are digital records that list a patient's diagnosis, prescriptions, food allergies, and test results together with their medical history. EHRs give medical professionals a comprehensive picture of a patient's health status, which is essential for correctly detecting and treating sepsis. EHRs also give clinicians the ability to track and keep track on sepsis development, including vital signs, test data, and medication usage. By determining where and by whom errors are being made, process mining can assist increase the accuracy of EHR data. Healthcare professionals can take action to lower the likelihood of errors, enhancing patient safety and the standard of care, by recognising these areas.

Clinical Decision Support (CDS) Systems: These computer-based tools support clinical decision-making by healthcare professionals. Based on patient-specific data, CDS systems can offer clinicians alerts, reminders, and recommendations. When it comes to sepsis, CDS systems can warn doctors about potential sepsis cases, suggest the best diagnostic procedures and therapies, and track the patient's therapeutic response. Process mining algorithms can find patterns in the data by examining the data produced by CDS systems, indicating where the CDS system is being used effectively and where it is not. Process mining, for instance, may show that healthcare providers are not consistently adhering to the CDS system's recommendations, indicating a need for extra training or education. As an alternative, process mining might spot places where the CDS system is giving too much direction, which would result in alarm fatigue and reduced effectiveness.

Real-time Location Systems (RTLS): RTLS tracks the whereabouts of people and things in real-time by combining several wireless technologies. RTLS can be used in hospitals to track

patients, employees, and equipment, which helps improve patient flow and shorten wait times. The use of RTLS in the context of sepsis allows for the tracking of patients' movements and whereabouts, which can be used to spot delays in admission and discharge. By giving insight into how the system is being used, where it is effective, and where changes can be made, process mining can assist healthcare providers in optimising their RTLS systems. Healthcare providers can enhance patient care, lower operating expenses, and ultimately enhance patient outcomes by optimising RTLS systems.

Mobile Health (mHealth) Solutions: Patients and healthcare professionals can obtain health information and connect with one other remotely thanks to mHealth solutions, which consist of mobile applications and devices. Sepsis-related mHealth solutions can be used to remotely monitor patients, educate, and support patients and their families, and improve provider-patient communication.

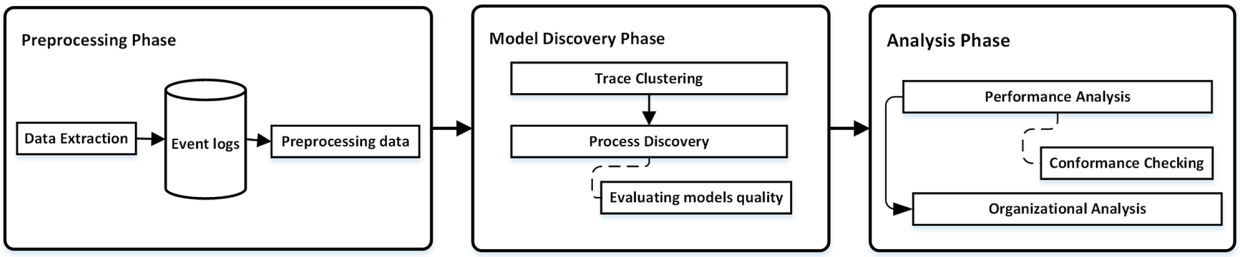
Artificial Intelligence (AI) and Machine Learning (ML): AI and ML are technologies that let computers make judgements based on data without having to be explicitly programmed. AI and ML may be used to analyse enormous databases of patient data in the context of sepsis, spot patterns and trends, and forecast outcomes. To identify individuals who are at a high risk of getting sepsis and to take early action, for instance, AI and ML can be used to create predictive models for the condition.

Process mining can be applied to various types of systems, whether they are purely information-based such as ERP systems or involve hardware, such as embedded systems. The essential requirement is that the system generates event logs that capture some or all of the system's behavior.

Implementation

The implementation plan that has been devised consists of three phases. In the first phase of Data preprocessing, the data from various sources such as Electronic Health Records (EHRs), Clinical Decision Support (CDS) systems, Real-Time Location Systems (RTLS), and mobile health (mHealth) systems is collected and cleaned to create an event log. In the second stage of Model Discovery, a process model that depicts the real process flow is created using the event log. To find process bottlenecks, inefficiencies, and variances, use the process model. The process model is examined in the final stage of analysis to find areas for process improvement. Techniques including simulation, optimisation, and what-if analysis may be used in the analysis.

*Data preprocessing***:** The initial step in this phase is to gather the event logs of a sepsis patient's admission to discharge process from numerous sources, including electronic health records, patient monitoring systems, nursing notes, and doctor's orders. The data is then preprocessed, which entails ensuring its quality and usability by cleaning, filtering, converting, and improving the data. Data cleansing, data transformation, data enrichment, and data integration are just a few of the tasks that fall under this phase. Data cleaning tries to eliminate discrepancies in data, such as missing or false data. The process of transforming data entails putting it in an analytically-friendly manner. Adding pertinent information to the data, such as patient demographics, clinical data, and diagnostic data, is known as data enrichment. To establish a cohesive view of the process, data from many sources are combined through data integration.



Note: Proposed methodology based on process mining for patient's careflows. (https://doi.org/10.1371/journal.pone.0281836.g002)

Model Discovery Phase: In this phase, a process model that depicts the admission to discharge process of a sepsis patient is created using the preprocessed data. Process discovery, conformance testing, and enhancement are some of the tasks included in this phase. Automatically creating a process model from the event logs is the goal of process discovery. Comparing the actual process behaviour to the anticipated behaviour based on the process model is known as conformance checking. Enhancement entails modifying the process model in accordance with the findings of the study to increase its precision and applicability. A process model that details the admission to discharge process of a sepsis patient is the product of this phase.

Phase of Analysis: In this phase, the process model is examined to find bottlenecks, inefficiencies, and areas where improvements can be made. Process improvement, root cause analysis, and performance analysis are some of the tasks included in this phase. Based on the process model, performance analysis seeks to assess the effectiveness of the admission to discharge process for a sepsis patient. Finding the fundamental reasons for process inefficiencies and bottlenecks is the goal of root cause analysis. Process improvement is figuring out how to make improvements to the process that will increase its effectiveness and efficiency. A list of suggestions for streamlining the admission to discharge process for a sepsis patient is the result of this phase.

These three process mining phases offer a methodical and data-driven methodology for analysing and improving the admission to discharge process.Throughout the entire process, we will observe the technology and assess its performance. Any deviation from the predefined criteria will be recorded for future analysis.

Critical Success Factors

Healthcare organisations should consider the following crucial success elements to optimise the admission to discharge process in an emergency room for incoming patients with sepsis using process mining:

1. **Data quality:** Through data governance and data management, healthcare organisations should make sure that the data used for process mining is correct, full, and consistent.

2. **Executive sponsorship:** The project's sponsors should be devoted to it and provide the necessary resources. Successful process mining requires a cross-functional team with a range of skills and knowledge, including members from the operational, clinical, and IT departments.

3. **Clear goals and objectives:** To ensure that the process mining project's findings can be put to use, the project team should set clear goals and objectives.

4. **Engagement of users:** To ensure that end users' demands are met, end users should be included in the project from the very beginning.

5. **Process standardisation:** To ensure consistency throughout the organisation, healthcare organisations should establish standard operating procedures and workflows.

6. **Change management:** To make sure that end users accept and use the process modifications, a change management plan should be created.

7. **Continuous improvement**: It is necessary to maintain the process' effectiveness and efficiency. Regular reviews and updates are therefore necessary.

Risks

Process mining can optimise the admission to discharge process for sepsis patients in emergency rooms, but there are certain risks associated with its application. Some of the risk factors that healthcare facilities should consider are listed below:

1. **Problems with data quality:** The accuracy of the data used in process mining is essential. Inaccurate process models and suggestions may result from incomplete, inaccurate, or inconsistent data. (Andrews et al., 1970)
2. **Data privacy and security:** Healthcare organizations must protect patient privacy and ensure that any data used for process mining is secure. Since the data could be sensitive and subject to regulations, this can be difficult (Jorge Munoz-Gama a et al., 2022).
3. **Resistance to change:** Employee resistance to change could prevent new procedures and technology from being adopted as quickly as they might otherwise.
4. **Complex Implementation:** Implementation of process mining can be challenging and time-consuming because it requires specialised knowledge and resources. Healthcare organisations must make sure they have enough funding and assistance to implement process mining technologies successfully.
5. **Results misinterpretation:** Poor inferences and suggestions can be drawn from process mining results that have been wrongly interpreted. Healthcare organisations must have the appropriate expertise to correctly evaluate and use the outcomes.

6. **Cost:** If the organisation needs to invest in new technologies, tools, and expertise, process mining adoption may be costly. To decide if process mining is a practical answer for their needs, healthcare organisations must carefully weigh the costs and benefits of the technology.

Process mining faces a number of challenges, but these challenges can also present opportunities for improvement. Proper implementation of process mining can lead to increased automation, more efficient collaboration, and more agile hospital systems.

Mitigation

There are various approaches to reduce the risks involved with using process mining to improve everything from a patient's admission to their discharge. Here are a few possible tactics:

1. **Data validation rules, data cleaning, and data integration** methodologies should all be used to guarantee the improvement and maintenance of data quality. By using data management tools and processes to guarantee the accuracy and completeness of the data, this can be accomplished.
2. **Data security and privacy**: Healthcare organisations should make sure that they abide by all applicable privacy rules and regulations, including HIPAA and the General Data Protection Regulation (GDPR). To protect patient data, they should also adopt data security procedures and encryption mechanisms.
3. **Communication and staff training:** educate staff about the advantages of process mining and how it might enhance patient outcomes. This will encourage staff employees to accept new procedures and technology and mitigate resistance to change.
4. **Knowledge and resources:** Ensure that the company has the expertise and resources necessary to successfully apply process mining solutions. Partnering with subject-matter specialists or funding employee training programs can help achieve this.
5. **Interpretation of the results:** Organisations should invest in gaining the knowledge required to interpret the results and use them effectively. This can be done by providing employees with training, working together with specialists, or recruiting consultants who have the necessary skill set.
6. **Cost-benefit analysis:** To ascertain whether process mining is a workable solution for the organisation, perform a complete cost-benefit analysis. This will make it easier for the organisation to compare the implementation's advantages and costs and decide whether it would be financially feasible. Employing a combination of these strategies will enable healthcare organisations to reduce the risks associated with implementing process mining.

By consistently adhering to these principles and monitoring them, we can stay mindful of potential biases and inequalities and take steps to prevent them from arising. Moreover, this approach will also enable us to inform patients about the usage of their personal information.

Conclusion

Given the severity of the sepsis disease worldwide, it was important to take action to optimize the admission to discharge process in an emergency room for incoming patients with sepsis to timely provide treatment.

We believe processing mining to be the ideal data analysis tool to implement and optimize the admission process for patients with sepsis. Process mining would help find deficiencies in the as-is process by comparing it to the to-be process. We further identified that the deficiencies would be solved by implementing automation within the process to optimize the admission to discharge process in an emergency room for incoming patients with sepsis. List of technologies that would be implemented are electronic health records, clinical decision support (CDS) systems, real-time location systems (RLS), mobile health (mHealth) solutions, artificial intelligence and machine learning.

We also conclude that process mining and automation will be implemented in three phases namely data preprocessing, model discovery and examination. Though process mining is a mature technology, there are risks associated with it. The top risks include problems with data quality, data privacy and security, complex implementation and misinterpretation of results. However, like most risks, severity of the risk will be mitigated through data validation rules, data cleaning, and data integration, data privacy and security and training.

Lastly, we believe that the benefits of process mining and automation would be far beyond the cost, saving millions of lives and dollars globally. It will create opportunities for improvement in the medical industry while optimizing the admission to discharge process in an emergency room for incoming patients with sepsis to timely provide treatment and hence, to solve the severity of sepsis, Bayers is strongly encouraged to implement process mining and automation.

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