Subpopulation process comparison for in-hospital treatment processes: a case study for sepsis treatment

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ABSTRACT

Within the hospital, different care paths are followed by patients diagnosed with sepsis, which is a life-threatening condition, predominantly caused by an infection. Current models of sepsis treatments do not take into account how care paths differ per subpopulation of patients and whether differences and similarities exist between multiple subpopulation processes. This research uses process mining to find and visualize differences in the treatments of different subpopulations within the patients diagnosed with sepsis. The aim is to find differences and similarities between the in-hospital treatment processes of the subpopulations. Using these results, interesting insights about sepsis treatment are obtained. Future research could go deeper into the treatment processes in correspondence with the hospital to perform better medically informed research. Further, it could investigate how to implement changes within the treatment based on the obtained results.

Additional Key Words and Phrases: Process Mining, Sepsis, Healthcare, Process Comparison

1 INTRODUCTION

The condition of sepsis is a life-threatening condition, which is often originated from an infection. The patients suffering from the disease are often elderly. The disease faces a mortality rate of 20% - 50% [7], while for patients with septic shock this percentage is even higher. The mean mortality rate of patients with hospital-based sepsis is 35% and 10 of 1000 patients come in with the sepsis diagnosis, of which 30% develop a multiple organ dysfunction syndrome (MODS) [19]. Next to the high mortality rate, the disease has the second-highest readmission rate and 18-26% of sepsis patients return to the hospital within 30 days [12]. Most research already existing goes into the biological indicators and predictors of the disease. Research shows that indicators of the occurrence and severity of the disease are existing. Age [15] and SIRS criteria [4] have shown to be predictors of the disease, which makes them interesting attributes to further investigate and to base subpopulations on. The duration of the treatment was chosen as the third splicing attribute. Between those subpopulations, the differences between process models are discussed. The differences have been analyzed by performing process mining techniques and comparing the mined process models to each other by using different plugins within ProM [32] and the BPMNDiffViz tool [9].

1.1 Problem Statement

Process Mining has been used to analyze different processes within healthcare. Earlier research has proven process mining to be a fitting way to analyze event logs of treatment of the condition of sepsis [8]. However, this has not yet been done while focusing on the subgroups of age and the severity of the sepsis condition. In this case, subgroups are sections of the dataset after being spliced on characteristics of the data subject. The focus lies on age and severity of the disease, as age has proven to be related to the number of persons that contracts the disease [15]. As sepsis is often occuring in high severity [12], the treatment process will be analyzed upon that characteristic too. Research is needed to improve the care quality and treatment for sepsis. Therefore, the results of process comparison could help design treatments to be more fitting to a certain subgroup, making them more efficient and improving the care quality.

1.2 Research questions

The problem statement described leads to the following main research question:

- **RQ:** Which differences can be found between treatment procedures for different subpopulations of patients with the condition of sepsis?

In order to be able to distinguish the differences between treatment procedures, the subpopulations should be defined first. As age has proven to be of influence on the likeliness of getting sick of sepsis, the groups will be divided among certain ages. Research and data exploration should point out which attributes will be used to divide the subpopulations by.

- **Subquestion 1:** How should the different subpopulations be divided?

Secondly, as the process models should not only be compared visually, as such a comparison would only provide a qualitative approach, a quantitative analysis should complement the results. Many different manners and tools exist to compare process models. Before comparing, the most suitable and sufficient tool should be researched and decided upon.

- **Subquestion 2:** Which process model comparison tool provides the best comparison?

After deciding upon these subpopulations and the comparison tool, the processes can be retrieved and analyzed. The processes should be compared visually, by comparing different metrics defining the conformance and performance of the process models. Lastly, the chosen tool should continue the comparison by providing a clear score based on the used metric.

- **Subquestion 3:** What are the different treatment processes for the different subpopulations?

The answer to subquestions 1 and 3 will provide the foundation to find the answer to the main research question, for which the process models and insights found in subquestions 2 will be used.

The remainder of this paper is structured as follows. Section 2 discusses the background of this research, covering process mining, sepsis and the tools used. Section 3 sheds light on related work that

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has been performed. The methodology used and the approach that is taken are discussed in section 4. Section 5 provides the results from the process model comparison. The discussion, which is section 6, poses concerns about the validity of this research and threats that may exist. Finally, the last section, section 7, concludes this research and discusses some future work

2 BACKGROUND

2.1 Process Mining

The main goal of process mining is to extract knowledge from data by mining event logs and storing information about activities performed [29]. The data is often retrieved from systems within a company logging the events or activities happening within processes, for example from an Enterprise Resource Planning (ERP), Business Process Management (BPM) or Product Data Management (PDM) system. This knowledge is then used to discover, monitor and improve the actual processes. This knowledge helps improve and evaluate the implementation and performance of the process and might even help configure additional requirements or steps that are currently not implemented [21][29]. Many different tools have been designed to help process mine, both commercial platforms such as Celonis, IBM Process Mining and UIPath Platform, and open-source platforms such as Disco and ProM.

Within the healthcare application, process mining could be used to support managerial decisions to improve the quality and reduce the costs of treatments. The quality of hospital services is dependent on the suitability and the efficiency of the processes executed, which makes a critical view and analysis of the processes within a hospital beneficial. The results may cause improvements in in-hospital treatment, which the quality of life of patients may be highly impacted with.

2.2 Sepsis

The condition of sepsis is often emanated by an infection as it is a medical emergency describing the systemic immunological response to an infection. It could even cause dysfunction of an organ [7]. Other causes of the disease include bacteria, severe trauma, viruses, fungi, parasites, or other incidents such as a urinal system infection [19]. In America, around 1,000,000 persons are affected by the illness each year and the illness holds a mortality rate between 28% and 50% of adult patients [16]. The diagnosis of sepsis is often found relatively late as there are quite some difficulties in recognizing, treating, and studying sepsis, even though early diagnosis and treatment are necessary for this condition due to high mortality rates. Research has been done regarding biomarkers indicating sepsis to ensure early discovery and treatment as to which the SIRS criteria have been established [22]. This indicator measures heart rate, temperature, respiratory rate, and number of white blood cells. When two of the indicators can be measured over the threshold of the indicator, the Systemic Inflammatory Response Syndrome (SIRS) is diagnosed. The diagnosis of sepsis holds when an infection is present or presumed for patients together with a SIRS diagnosis [20]. The diagnosis is converted to severe sepsis when organ dysfunction or hypo-perfusion, which means an increased blood flow through an organ, starts occurring. The last and most severe phase will then be a septic shock for which severe hemodynamic failure occurs, which means that the blood fails to stream in the correct way[5].

Earlier research has shown that a relation between readmission and the mortality rate is existing [12]. It was pointed out that sepsis has the second-highest readmission rate among Medicare Beneficiaries and that 30-day readmissions occur for 18-26% of released sepsis patients. The mortality rates for the patients suffering such a readmission range from 6.5–14.4%.

2.3 Tools

To be able to perform process mining a process mining tool is required. In this case, the process mining framework PRoM is used which works with different plugins, making it possible to perform different sorts of analyses. The plug-ins that are used are the "Filter Event Log", "Filter Log by Attributes", "Inductive Visual Miner" (IvM) and the "Convert Petrinet to BPMN" plugin. The first and second plugins are essential in this research as they allow for the separation of the event log into subsections. The third plugin helps to mine. It creates Petri nets, on which the tool allows to replay actual behaviour. Performance and conformance details can be retrieved from these tools, which help compare the process models on the duration of the actual behaviour and how well the process models fit the actual behaviour. The "Convert Petrinet to BPMN" logically alleviates creating a BPMN, which is required for comparing the models, by automatically converting the Petri net to a BPMN.

The plugins mentioned, allow for visual comparison of the models. Further, by using the metrics retrieved from performing performance and conformance analysis, the start of the quantitative comparison analysis is constructed. The BPMNDiffViz tool [9] is used to take the quantitative comparison analysis further. This tool has been created specifically for process model comparison, precisely for business process models. Within the tool, the graph edit distance (GED from now on) is calculated between two process models.

3 RELATED WORK

3.1 Hospital Treatment of Sepsis

As this research covers the care paths of sepsis patients, it is necessary to find out what the current state of research is for the treatment and whether it can be identified within the data used in this research.

Over the last three decades, there have been quite some changes within the treatment of Sepsis due to extensive research into psychophysiology. It has been found that the early diagnoses, treatment and care of patients are of great importance[7]. Research on biomarkers should provide scoring systems indicating the likeliness of getting ill, which has been performed and is still going on. In addition to that, they should help in early discovery, identifying high-risk patient populations and monitoring the disease [22]. The most evident biomarkers currently in use are the SIRS criteria, which consist of 4 criteria. The first criterium is met when a persons' temperature is lower than 36 or higher than 38 °C, the second when their heart beats over 90 times per minute, the third when their respiratory frequency is over 20 breaths per minute and the fourth is met when the amount of white blood cells (10^3/µL) is lower than 4 or higher than 12 [4].

Improvements within the treatment have been applied over the last decades, in which antibiotics and cardiovascular treatment especially are of great importance. The first six hours are really important as appropriate antibiotic treatment in these first hours can halve the shock incidence. Metabolic support should be provided to sepsis patients to make sure that the patients' body has enough energy to fight the inflammation and when needed organ-supporting treatments, should be provided. Concluding, much experimental research has been performed and still much research is needed to improve the treatment of sepsis and reduce the mortality rate [19].

3.2 Comparative Analysis using Process Mining

Both the articles [10] and [31] write about comparative process analysis, showing methods that can be used to split the data into subpopulations. A method is proposed that allows for splitting the process data into different cubes by slicing, dicing, rolling up or drilling down the data into *process cubes*. The attributes of the event data are used to divide the event data. Slicing means that an attribute is chosen over which the data will be split into samples all holding a different value for that attribute. With dicing, several attributes will be chosen that the dataset will be split upon. These techniques help to create smaller datasets. The subpopulations within this research are created by slicing the data based on attributes.

3.3 Process Mining in Health Care

As this research performs process mining on a process within health care, it is necessary to find out what has already been done within this area and to learn from others' practices. Within hospitals data about the care and treatments is saved within a Hospital Information System (HIS). This data can be used to perform process mining to gain more insights into the processes within a hospital. Research can focus on finding the bottlenecks, most followed paths and so many more objectives. The information gained from the process mining can then be used to improve and optimize the processes [21].

Research on the use of process mining within health care has been performed multiple times. As the process models of treatments in a hospital are often not planned like industrial processes are, modelling the processes often results in spaghetti-like models, meaning that the models have a high complexity. These processes are hard to understand and analyze [33]. Therefore, process mining practices should be reevaluated before using them within health care. As BPMN modelling has shown to be useful for modelling clinical pathways, which is a recent development in medicine, BPMN modelling is used to create the base models in this research [23].

Another paper [17] writes about the comparison of processes between four different Australian hospitals. Within this research, a comparison was done based on service performance and efficiency indicators and creating one common model including the paths of all patients within the different hospitals using the "Fuzzy Miner" plugin in ProM. By the comparison within the research delivered some interesting insights were gained, however, it was mentioned too that getting all processes to fit together into one model was a challenge, which is why in this research another approach is taken.

Work of [12] describes the usages and usefulness of process mining techniques within Health Care. By performing the analysis of the process of stroke care based on clinical data in ProM, it shows that interesting insights regarding the comparison of different hospitals and different subpopulations of the patients can be found. It shows that bottlenecks can be found and investigated.

Work of [14] describes the comparison of the cancer treatment process within two different hospitals. It is found that average fitness can be a good indicator of visual similarity, while average precision and graph edit distance are found to be strongly correlated with the visual impression.

In another related work, [28] the comparison is made between the processes of subpopulations within patients with heart failure by using ProM and the BPMNDiffViz tool. The subpopulations are based on age and blood pressure. The research shows that the process of the oldest age groups differs the most from the other processes.

The work [8] performs exploratory process mining on the 4TU Sepsis dataset, by using the ProM platform. The "Alpha Miner" and "Discovery Matrix" plugins were used. It was found that the ProM platform was useful and the process mining techniques appear to be effective in performing process mining on the hospital data event log. Additionally, it was found that events *Leucocytes* and *CRP* are the most performed within the data, and additionally, the Discovery Matrix shows that both have a causal relationship with the release events. *Admission NC, ER Registration, IV Anti-biotics* and *IV Liquids* have shown to have a causal relationship with Admission to the IC. The research writes that not only the steps a patient takes should be analyzed, but that the profile of the patient is of importance too. It is stated that the steps taken by patients re-admitted to the ER should be analyzed concerning their profile [8], which is attempted within this research.

4 APPROACH

The approach taken in research consists of 6 phases, based on the PM^{2}HC methodology [18], which is based on the PM^2 [30] process mining methodology. The difference between the two is that the PM^{2}HC methodology is more specified towards health care processes, hence better suiting in this case.

4.1 First phase: Research Planning

The first phase consists of planning the research. During this phase, a process is selected that will be used as a base for the research. For this research, the treatment process of sepsis will be evaluated. Second, the research questions should be identified as well as the goals of the research. Within this phase, it should be decided to which extent and with which metrics the process models should be compared. Furthermore, the platform for performing process exploration and process mining should be decided upon. In this research, the process models will be compared by using BPMNDiffViz, which delivers a graph edit distance as the metric [9]. The ProM [32] platform is used for process exploration and process mining. In this phase, the research proposal was written too.

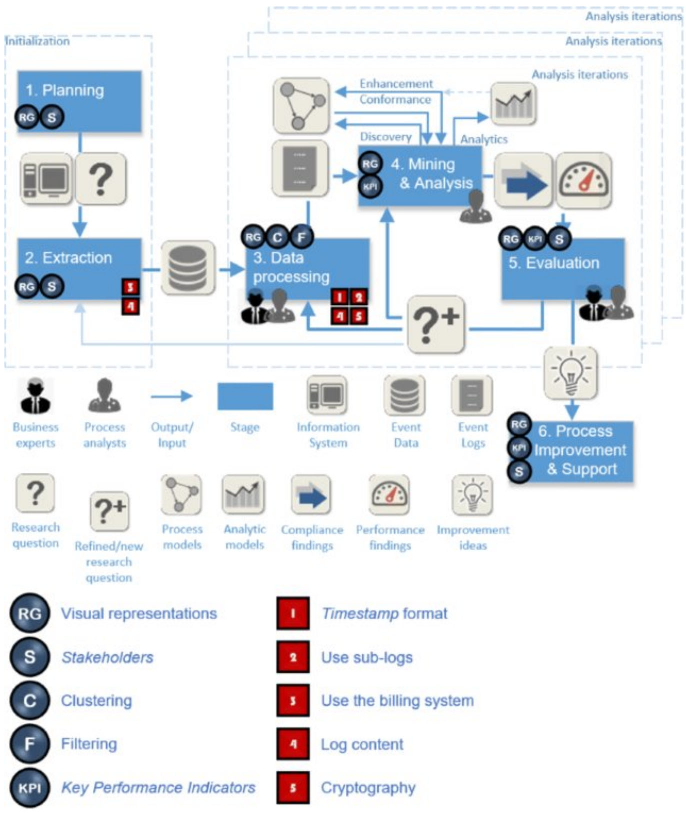

Fig. 1. Visualization of the PM^{2}HC methodology

4.2 Second phase: Extraction

During the extraction phase, which is the second, is determined what will be within and what will be left out of the scope of the research. The required event data will be extracted and retrieved. In this research, the data used is retrieved from the 4TU research data platform [11]. It contains real-life events of sepsis cases from a hospital, specifically of patients that were entering the emergency room [8]. Every trace represents the pathway of a case through the hospital. In totality, the dataset consists of approximately 1000 cases with in total of 15,000 recorded events. 39 attributes were recorded of which certain values were anonymized.

Within the scope of the research will be to compare the process models of the identified subpopulations, assisted by the comparison tool that is most adequate to this research. Lastly, as sepsis is known for its high mortality rate, the process is investigated to see whether it shows any peculiarities regarding long treatment or mortality.

4.3 Third phase: Data processing

The next phase is part of a more substantive iterative analysis phase as one is expected to go back and forth between the third, fourth and fifth phases. The data is processed by creating visualizations of the processes. Usual steps within this phase would be the aggregation of the events and filtering and enrichment of the logs. The attributes that will be used are the name of the event, timestamps, age of the patients and an attribute indicating whether the SIRS criteria holds 2 or less. The visualizations made are used to get more insight into the event log, which is provided by dotted charts and visualizations of the process models. The event log used does not need any enrichment, so only filtering is done. The event log was inputted as an XES file into the ProM platform. Next, the file was filtered into the subpopulations in the "Filter Event Log" and the "Filter Log by Attributes" plugin.

4.3.1 ***Subpopulation Selection.*** Within this data processing phase, the first research question is answered. By discovering the data in the "LogVisualiser (LogDialog)" plugin and performing literature research, interesting attributes should be found, on which the subpopulations should be based. The data should be sliced into cubes of data based on (a combination of) attributes [10].

4.4 Fourth phase: Mining Analysis

The fourth phase focuses on mining and the analysis of the process data. The main goal of this phase is to gain information on the different treatment paths and to discover the different care paths by mining the processes. More insights are gained by performing performance analysis and the models created are checked by performing conformance analysis. Within this phase, the process models will be analyzed and compared to the processes of the other subgroups.

In order to be able to perform any comparisons, the filtered event logs had to go through some preparation within ProM. The filtered subpopulation event logs were taken and turned into a Petri net by using the "Mine Petri Net with Inductive Miner". Secondly, these Petri nets were turned into BPMN models by using the "Convert Petri Net to BPMN" plugin. The resulting BPMN models were then taken into the BPMNDiffViz tool in which the models were compared.

Next to the comparison, the process models were inspected using the "Inductive Visual Miner" plugin. This ProM plugin allows for analysing the number of persons following certain activities, finding the relative paths and following bottlenecks. Next to that, the tool allows for performance and conformance analysis. In this case, the behaviour of the patients against the process model of their assigned subpopulation was measured.

4.5 Fifth phase: Evaluation

The next phase, which is the last phase within the phase of iterative analysis, evaluates the results found in the mining and analysis. The goal is to gain insight into the processes within the sepsis treatment and to translate the numerical values into new ideas and conclusions.

The results retrieved from the comparisons within BPMNDiffViz and the inspections within the "Inductive Visual Miner" plugin were translated into textual conclusions.

4.6 Sixth phase: Improvement & Support

The last phase focuses on the evaluation of the research of which it is the goal to find future implementation plans and ideas. The main goal is to provide ideas and plans for the future based on the findings from the research. All results will be evaluated and interpreted in this phase. As this is the last phase, the actual implementation is not included in this research. The results obtained can be used by stakeholders to develop them into plans and improvements.

5 FINDINGS

5.1 Division of subpopulations

As described earlier, the subpopulations have been divided by researching the attributes and their relation to the sepsis diagnosis and the severity that the attribute should indicate. The data includes 31 attributes, mostly indicating blood values and diagnoses. The attributes used for dividing the data into different subpopulations are in this research *age*, and whether 2 or more of the SIRS criteria are met (*SIRS criteria ≥2*). An attribute that is not included as an event attribute already, but is calculable, is the *duration of a treatment process*, specifically whether a process takes more or less than 7 days. For this attribute, only the beginning or finishing times of the activities are included, which means that the total duration cannot be assumed. The difference between the beginning of the treatment and the end registered can be taken as the duration however. Within the logged patients, the average age is 70.07. In order to create subpopulations of approximately equal size, the event log is sliced at the age of 65 and 85, resulting in three subpopulations of which the first contains the traces of patients with age ≤ 65 years old, the second age >65 and <85, and the third holds patients with age ≥84. Over half of the patients in the US in the Intensive Care are over 65 of which many suffer life-threatening sepsis [27], which is why the age of 65 is taken as a threshold for the first and second subpopulation. As the values for whether the SIRS criteria can only be true or false, the dataset was spliced into two cubes.

5.2 Comparison tools

In order to find the best suiting process model comparison tool, several tools have been explored and compared in terms of precision, use and metrics. For process model comparison three kinds of metrics can be identified. For all sorts of similarities the event labels, i.e. the event names, are considered. For node matching similarity, the attributes of the events within the processes are considered as well, whereas, for structural similarity, the focus lies on the topology of the process models. Lastly, in behavioural similarity causal relations are captured as well [6].

5.2.1 BPMNDiffViz. The BPMNDiffViz tool is a web-based platform which lets its user compare two business process models and visualize them. The tool provides structural matching by visualizing the graph differences and providing statistics to assist in analyzing the differences between models. Within the tool, the minimum graph edit distance between two processes is calculated. These calculations are based on the number of transformations within a process that should be performed to transform one process into another by using the event labels of activity nodes [9]. Both structural and label matching metrics are thus used to calculate the differences. Within BPMNDiffViz several algorithms are implemented that help compare the process models. The first of these algorithms is the greedy algorithm, which is the default and the simplest algorithm [24]. The simulated annealing algorithm is more complex, using a notion called temperatures to select random neighbouring solutions and assess the probability that the solution will be chosen, based on the temperature [24]. Other implemented algorithms are the Genetic, AStar, Ants and the Tabu Search algorithm. The Tabu Search algorithm finds the minimum graph edit distance by moving through a graph of solutions. Within this graph, it searches for the best neighbouring solution at each time. Solutions that were considered already end up in a list to reduce the looping times. In addition, the algorithm limits the size of the list and the overall number of steps to improve the performance. The solutions with the minimal costs are selected to find the overall minimal costs. Whenever this has been found or the maximum number of steps has been reached, the solution is presented [25].

Lastly, the process models can be compared quantitatively using another metric than the graph edit distance metric calculated by a tool. Performance and conformance metrics [1][13] can be designed to compare the paths going through a process model, think of average duration, the fitness of a model, waiting times and the number of procedures per patient [14].

The tool that is chosen and used in this research is the BPMNDiffViz platform as it provides clear visualizations and GED scores for a quantitative comparison. Research has written that the Tabu Search algorithm provides more precise results and that it is faster than the other algorithms discussed [24], which is why it has been chosen to be the used algorithm in this research. Next to the comparison using the BPMNDiffViz tool, conformance checking is performed by comparing the percentage of total traces performing a certain activity within a subpopulation. This comparison analysis shows which subpopulation is most likely to follow a certain activity.

5.3 Comparison of treatment processes

The subpopulations are compared by using BPMNDiffViz, which calculates the graph edit distance between two Business Process Models and visualizes the differences. The models are compared upon the attribute the subpopulation was sliced on. Some of the activities within the process models are analyzed further and compared upon conformance. The models created in ProM and BPMNDiffViz are stored on the author's GitHub [1].

In general, all of the models include at least 12 activities and 16 at most. Most however include either 14 or 16. For all the activities *ER Registration* and *ER Triage* happen at the start in parallel. The *Release Activities (A, B, C, D, E)* all happen close to the end event as often it is the end of the treatment. Only the *Return ER* occurs after a patient has been released in any form. In general, 63.8% of all patients go through *Release A*, while *Release B, C, D and E* altogether are only followed by approximately 5.5% of all patients. The activities *CRP* and *leucocytes* are for all processes the most accessed activities, often more than once in a single process. Leucocytes is an activity involving either measuring or treatment of the white blood cells [3], and CRP tests the amount of C-reactive proteins the patients have, which is made by the liver as a reaction to an inflammation [26]. The activities *LacticAcid, IV Liquid, ER Sepsis*

[1] https://github.com/floorrademaker/SepsisComparisonModels

Table 1. Division of subpopulations

Attribute	Subpopulation 1	Subpopulation 2	Subpopulation 3
Age	≤ 65	>65 and <85	≥ 85
SIRS criteria ≥2	True	False	/
Process Duration	Less than 7 days	More than 7 days	/

Triage, AdmissionNC and IV Antibiotics occur in each process model. The included release activities (*Release A, B, C, D, E and Return ER*) are different for every process model and *Admission IC* is not included in all of the models. In total, 28% of all process traces include the *Return ER* of which 27.7% of those traces it is the end event.

For the comparison of the process models of the subpopulations, the GED is calculated, indicating the transformations required to turn one model into the other. Next to that, the number of traces following the leucocytes and CRP event is analyzed and displayed at the number of occurrences divided by the number of patients within a subpopulation. As some events occur multiple times within one process, these percentages get up to values above 100%. The values of all processes for CRP and leucocytes are visualized in figure 4.

As the mortality rate and return rate of sepsis patients are higher than for most diseases, the mostly followed release activity and the returns of patients to the ER will be regarded for the subpopulations. The number of traces, i.e. the total amount occurrences of an event within a subpopulation divided by the amount of patients, following Release A and Return to ER are analyzed. Additionally per subpopulation, the number of traces following Release A that eventually return to the ER are compared. The results are visualized in figure 5.

5.3.1 Age. The age attribute accounts for three different subpopulations, thus three models. The GED for the comparison of 'Age $\leq$ 65' and 'Age >65 and <85' is 72. The model of this comparison is included as figure 2. The comparison of 'Age $\leq$ 65' and 'Age $\geq$ 85' results in 60 edits. Lastly, 'Age >65 and <85' and 'Age $\geq$ 85' has a GED of 42. The process models of the two oldest groups show the most differences. However, for the behaviour of the process traces following the model, the subpopulations are more similar. A part of he process model of the 'Age $\leq$ 65' subpopulation is included as figure 3.

As mentioned, leucocytes and CRP are the most accessed activities within this process. For 'Age $\leq$ 65' leucocytes have been performed 282.30% of the total amount of traces and CRP 273.1%, as can be seen in figure 4. For 'Age >65 and <85', this is 346% for CRP and 369.8% for leucocytes. Lastly, for 'Age $\geq$ 85' CRP is performed 308.9% and leucocytes 307.6%. With rise of age, a slight increase in the occurrence of both leucocytes and CRP can be observed.

Comparing the way of releasing between the three models, the largest differences can be seen between 'Age $\leq$ 65' and 'Age >65 and <85'. For Release A, Of which returns to the ER and Return ER (Overall) 'Age >65 and <85' has the highest amount of traces following the events. Then for both ER events, 'Age $\geq$ 85' follows. For 'Age $\leq$ 65' the least returns to the ER.

5.3.2 SIRS Criteria. The GED resulting from comparing the two models results in a GED of 58. For the subpopulation 'SIRS < 2', so having met less than 2 of the SIRS criteria, the mean of different included classes is 6, while for 'SIRS > 2' this is 10. Overall, the processes for patients for whom the SIRS Criteria is higher than 2 tend to go through more different events.

For 'SIRS < 2',the occurrences of CRP and Leucocytes are lower in comparison to the processes of the rest of the subpopulations, namely for 78.2% (CRP) and 80.7% (leucocytes) of the traces the events occur. Meanwhile, for *SIRS >2*, 336.7% of the traces enter CRP, and 346.8% enter leucocytes.

For the patients in 'SIRS > 2' 70.1% released through Release A, of which 41.6% returned to the ER again. Of the whole subpopulation, 31.1% returns to the ER again. For 'SIRS < 2' the amount of patients releasing through A and returning to the ER is halved percentually. In both 'SIRS > 2' and 'SIRS < 2', everyone who returns to the ER has been admitted to the NC earlier in the treatment.

5.3.3 Process Duration. Comparing treatments that take longer than a week (7 days) to shorter than a week cost 98 edits. The maximum activities that are included by the two models also differ as the treatments that have a duration of less than a week include 12 different activities, while for the longer treatment all kinds of activities are included (16). Within the shorter treatments, Release B and Release D are not included. Return ER is not included either, so we can conclude that no returns happen in the same week as a patient has entered the hospital. For the treatments taking longer than a week, the return rate is highest (63.5%) of all subpopulations, while for the treatments taking less than a week, no returns occur. The minimum time for a return is 7 days and 11 hours, so as observed no returns occur within a week. On average, however, a patient returns after 91 days.

6 DISCUSSION

The approach taken in this research will be reflected upon in this discussion. The described regards within this discussion should be taken into account when using the results of this research in order to ensure validity.

First, the knowledge of the sepsis disease of the author was limited. Research has been performed to become more acquainted with the disease and its treatment, however, the knowledge is still limited. Therefore, conclusions cannot be drawn about any medical details. Peculiarities in the treatment might not be recognized.

The data used within the research included the different events of the sepsis in-hospital treatment, however it was rather limited. Attributes such as age, blood rates and diagnoses where only assessed once in the whole process, limiting the possibility to perform any analysis on differences in attributes throughout the process. The

Table 2. GEDs retrieved by comparing process models

Attribute	Subpopulation 1	Subpopulation 2	Number of Edits
Age	≤ 65	>65 and <85	72
Age	≤ 65	≥ 85	42
Age	>65 and <85	≥ 85	60
SIRS criteria ≥2	True	False	58
Process Duration	Less than 7 days	More than 7 days	98

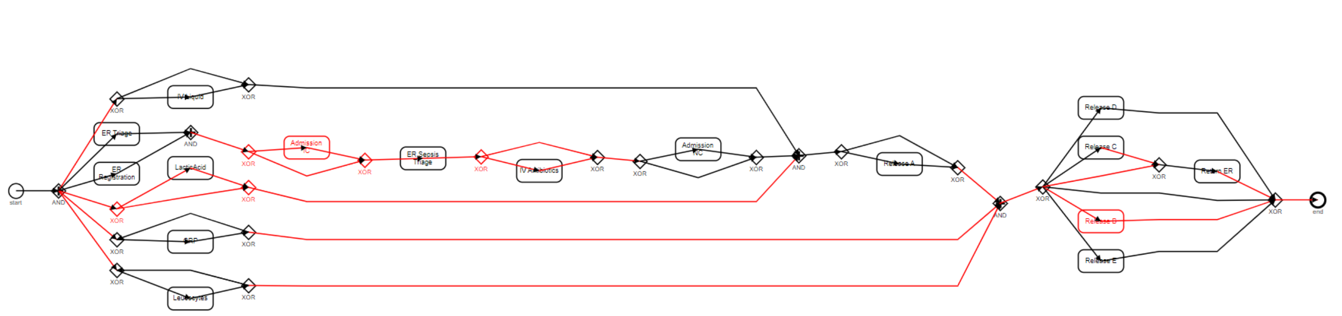

Fig. 2. Visualized Comparison of the process model for subpopulation 'Age ≤ 65' against 'Age >65 and <85', for which the red lines show relations and events that should be deleted to transform one process model into another. The black lines show the equal events and relations. *Retrieved from BPMNDiffViz.* Other comparison models can be obtained via[1].

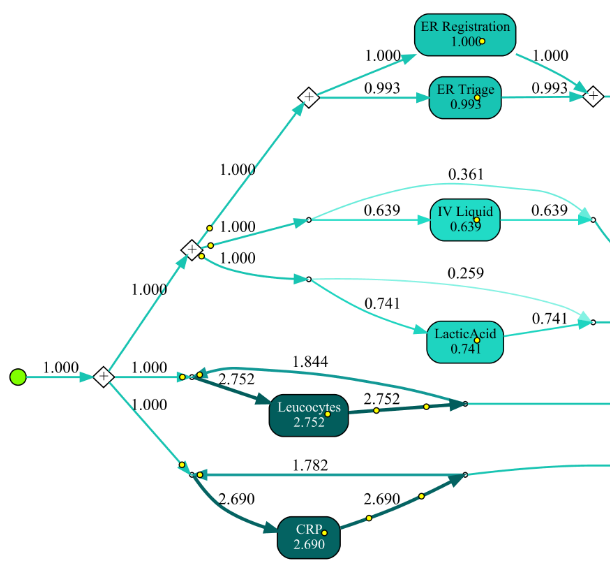

Fig. 3. Part of the process model of patients with age ≤ 65, mined with the Inductive Visual Miner (IvM) plugin. The whole process and all other process models are accessible via[1].

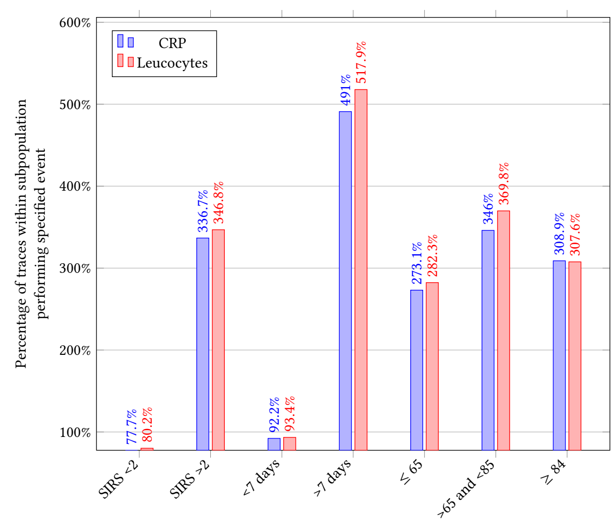

Fig. 4. Conformance Checking Activity Comparison for CRP and Leucocytes

dataset had been anonymized up until the point that the gender of the patients was not specified. Knowing the gender of the patient had and their origin could have led to more interesting insights.

As the data was obtained from an unknown hospital, no genuine conclusions could be drawn from the insights gained within the research. Even for the hospital itself the insights gained could be influenced by the year of the data, the way it was documented or any other bias. As the hospital is unclear no statements could be made with full confidence and foundation. The research does show the possibility of comparing process models within a hospital by using the GED metric and by conformance metrics.

If the research was performed in collaboration with the hospital, the results could verified and the hospital itself could clarify and

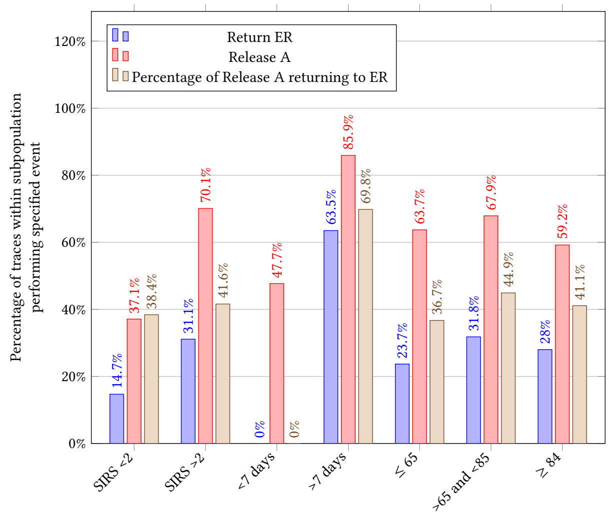

Fig. 5. Conformance Checking Activity Comparison for Release A and Return ER

elaborate upon their treatment process and possible bottlenecks or peculiarities.

As the mortality rate of sepsis is undesirably high, it would be interesting to gain insights into the processes leading to a person to decease. This however was not specified in the process. It could be obtained by removing all patients that were release through a release event and did not return to the ER. However, no conclusions could be drawn with any certainty, as someone not being release could also indicate steps in the treatment that were not documented or could have any other unknown reason.

Process mining is often associated with finding bottlenecks and making processes more efficient [2]. Within a hospital treatment process, one should be careful trying to make processes more efficient as it might endanger human lives. The results of this research should therefore be used to improve treatments instead of making them more efficient. Coming back to not knowing the hospital, thus not which stakeholders are included conflicts the goal of the research. The results obtained could be useful for the hospital or employees within the hospital, however no level of abstraction and no specific problems has been decided on as there has not been any correspondence with the hospital.

Finally, the comparison metrics within the research include the calculation of the GED through BPMNDiffViz and a conformance based on the percentage of a subpopulation performing an event in the process model. Even though conformance metrics have proven to be useful in process mining, mostly as an indicator for conformance, it has not yet been used to compare process models of subpopulations and it effectivity has not been proven yet.

7 CONCLUSIONS & FUTURE RESEARCH

The objective of this research was to find subpopulations of which the process models were compared. A comparison tool to compare the process models of these subpopulations was researched, compared and chosen. The subpopulations were based on age, including three subpopulations of which the first included all patients with age ≤ 65, the second all patients with age >65 and <85 and the last subpopulation included all patients with age ≥ 85. The second comparison involved two subpopulations of patients having met either two or more of the SIRS criteria or not. Lastly, a comparison was made between processes having a duration of either more or less than 7 days. The comparisons were made by calculating the GED of the process models through the BPMNDiffViz tool.

The largest obtained difference was the difference between the process duration subpopulations, with a GED of 98. Further, the subpopulation with a duration > 7 days obtained the highest occurrence of activites CRP and leucocytes, but also the Return ER and Release A activities. The percentage of patients going through both Release A and Return ER was highest too for this subpopulation.

For the age subpopulations, subpopulation 'Age >65 and <85' scored highest on all activities. For CRP and Leucocytes, the difference with the other age subpopulations was more substantial than for the releasing activities. The comparison model of the process models of 'Age ≤ 65' and 'Age ≥ 85' was most similar as it only required 42 edits to transform the one model into the other.

Release A was substantially more accessed than any other release activity. In general, 28% of patients return to the ER after being treated, however a ER return minimally happens after a week after the start of the treatment. The SIRS criteria have shown to be an indicator of a patient needing more treatment as the occurrence of events per patients have approximately doubled for 'SIRS criteria 2' in comparison to 'SIRS criteria <2'.

The results that have been found during the process mining analysis phase and the conclusions that come with it can be used by the hospital which has created the data used to further investigate the treatment process of sepsis. Future research could go deeper into the different events and attributes, and the causes of the differences. Bottlenecks could be investigated or different subpopulations could be evaluated to compare those processes. In correspondence with the hospital, information regarding the actual treatments could be obtained or an actual problem within the treatment could be investigated. This way, the research would be more informed and the results better well-grounded. Further, future research could investigate the validity of the conformance metric used in this research, whether it could be used in more practices and what kind of insights it could bring.

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