Made available by Hasselt University Library in https://documentserver.uhasselt.be

Process mining in healthcare – An updated perspective on the state of the art

Peer-reviewed author version

DE ROOCK, Emmelien & MARTIN, Niels (2022) Process mining in healthcare – An updated perspective on the state of the art. In: Journal of Biomedical Informatics, 127 (Art N° 103995).

DOI: 10.1016/j.jbi.2022.103995 Handle: http://hdl.handle.net/1942/36590

Process mining in healthcare – an updated perspective on the state of the art

Emmelien De Roock^{a,b}, Niels Martin^{b,c}

^a Vrije Universiteit Brussel, Data Analytics Laboratory, Pleinlaan 2, 1050, Elsene, Belgium ^bHasselt University, Research group Business Informatics, Martelarenlaan 42, 3500, Hasselt, Belgium ^cResearch Foundation Flanders (FWO), Egmontstraat 5, 1000, Brussels, Belgium

Abstract

Process mining is the research domain focusing on the development of innovative methods to gather insights from event logs. It has been used for various use cases within the healthcare domain with the ambition to instigate evidence-based process improvement. Over the past years, the research interest in process mining in healthcare has been increasing. This paper presents the results of an extensive systematic literature review on process mining in healthcare in which 263 papers have been reviewed. Besides providing the most recent overview of literature and the extensive number of reviewed papers, we complement existing reviews by considering three novel review dimensions: (i) the process mining project stages, (ii) the involvement of domain expertise, and (iii) the Key Performance Indicators (KPI) considered during the process mining analysis. Orthogonal to these three novel dimensions, we also highlight the evolution of the research domain by

^{©2022.} This manuscript version is made available under the CC-BY-NC-ND 4.0 license https://creativecommons.org/licenses/by-nc-nd/4.0/. The final authenticated version is available online at: https://doi.org/10.1016/j.jbi.2022.103995.

considering time trends within the review dimensions. The review generates new perspectives on process mining in healthcare as a research domain. For instance, process redesign is rarely part of a process mining project, domain experts are mostly asked for validating insights, and less than half of the published papers considers one or more specific KPIs to direct their analysis. *Keywords:* process mining, literature review, healthcare, event logs

1. Introduction

Within a healthcare organization, such as a hospital, a wide variety of processes are being executed. A basic distinction can be made between clinical processes (e.g. a medical treatment process) and organizational processes (e.g. a billing process) [1]. As the execution of many processes is supported by various types of health information systems, process execution data are being recorded in their databases. This process execution data can be used to build up event logs, which highlight when activities have been performed in the process, for whom they were executed (e.g. for which patient) and potentially even by whom (e.g. by which healthcare professional) [2–4]. The analysis of event logs can provide valuable information about how a healthcare process is being executed in reality. Process mining is the research domain focusing on the development of innovative methods to gather insights in processes from event logs [2, 4].

Process mining techniques have been used for various use cases within the healthcare domain. Examples include discovering the actual order of activities in the treatment trajectory of a patient [5], assessing to which extent clinical guidelines have been followed [6], and predicting the patient outcome based on how the process is being executed [7]. When using process mining within a healthcare context, the particularities of healthcare processes need to be taken into consideration. This includes their knowledge-intensive character [8] and the fact that they typically display high levels of variation [9]. While the complex nature of healthcare processes makes research on process mining in healthcare challenging, the potential of process mining to instigate evidence-based process improvement in healthcare highlights the great value of innovative research in this area [4].

The origins of process mining in healthcare date back to the beginning of this century. One of the earlier papers focusing on process mining in a healthcare context has been published in 2001 [10]. In the years that followed, novel process mining techniques were developed, which were also used in the healthcare field, surfacing challenges such as the high variability in process execution [11]. This has led to common references to healthcare as a challenging, but inspiring use case for process mining research [12–14]. Over the past years, the research interest on process mining in healthcare has significantly increased. This is demonstrated by the several literature reviews that have been published within the domain since 2016. These reviews either consider healthcare in general [3, 11, 15–18] or focus on a particular subdomain such as a specific set of medical conditions [19–22].

This paper presents the results of a novel systematic literature review on process mining in healthcare, which clearly distinguishes itself from prior reviews. Besides providing the most recent overview of literature and the extensive number of reviewed papers, we consider three novel review dimensions which have not been studied before: (i) the process mining project stages, (ii) the involvement of domain expertise, and (iii) the Key Performance Indicators (KPIs) considered during the process mining analysis. Orthogonal to these three novel dimensions, we also highlight the evolution of the research domain by considering time trends within the review dimensions, which also constitutes a novelty compared to existing reviews.

By classifying literature on process mining in healthcare according to these novel dimensions, new perspectives on the research field are provided in a substantiated way. When classifying literature according to the process mining project stages by Aguirre et al. [23], we show that an important part of published research on process mining in healthcare does not start from a specific healthcare research question. Moreover, there is fairly limited attention for explicit reporting regarding data preparation and process redesign is only considered in a small fraction of published work. Concerning the involvement of domain experts, our review highlights that a very small number of papers reports on consultations with domain experts throughout the various phases of a process mining project. Experts are the most frequently involved in the validation of insights originating from the analysis. With respect to the KPIs considered during the analysis, we demonstrate that the majority of the reviewed papers does not consider a specific KPI when conducting a process mining analysis.

The remainder of this paper is structured as follows. Section 2 outlines the preliminaries, including an introduction to process mining and an overview of the existing literature reviews on process mining in healthcare. Section 3 describes the used methodology of this review. Section 4 presents the results of the literature review according to the different review dimensions. Section 5 discusses the results and provides recommendations for the research field. The paper ends with a conclusion in Section 6.

2. Preliminaries

2.1. Introduction to process mining

As highlighted in the introduction, process mining focuses on the development of innovative methods to gather insights from event logs. Hence, the event log constitutes the key input for process mining [2, 4]. An event log minimally contains an ordered set of events for each case (e.g. a patient), but can also include other attributes such as the timestamp indicating when an event took place and the resources associated to the event [2]. Table 1 illustrates the typical structure of an event log, considering the fictitious context of a neurology department. Each entry in this event log represents an event, which is described by a number of attributes. The attributes included in Table 1 are [2]:

- Case identifier or case id: the unique identifier of the case such as the patient;
- **Timestamp**: the moment at which the event was recorded in the system;
- Activity: the label referring to the activity that was performed. In this example there are six different activity labels, namely: registration, CT scan available, EEG test, consultation, urine test, and discharge;
- **Transaction type**: the status of the activity. In this example an event either represents the start or the completion of the activity, i.e. the transaction types are "start" or "complete";

• **Resource**: the staff member or medical device associated to the execution of the activity. In the example there are eight distinct employees involved across the events.

Besides the aforementioned attributes, other details about the cases or events can be recorded in the event log, e.g. the patient's age or the diagnosis [4].

As highlighted above, each row in Table 1 depicts an event. For instance: the first event shows that the registration of patient with case id 5302 by receptionist Monica started on August 23rd at 08:51:33. The fourth event represents the corresponding completion event, i.e. the registration of patient 5302 was completed at 08:55:01. Afterwards, the same patient 5302 starts the consultation with neurologist William at 09:02:46.

Figure 1 positions process mining in healthcare in a larger whole. Healthcare processes typically generate large amounts of data through interactions between doctors, nurses, patients, and other stakeholders. Healthcare processes are increasingly being supported and controlled by health information systems, which store process execution data. Process execution data can be used to construct event logs, of which the key building blocks are exemplified in Table 1. These event logs can be used for process mining in different ways, where van der Aalst et al. [2] distinguish three types of process mining: discovery, conformance, and enhancement. Discovery starts from event logs and generates a process model. Conformance checking will compare an existing model with the event log, highlighting correspondence and deviations between the process model and the event log. Enhancement technique is used to extend, improve or repair a process model, e.g. to use it to perform simulation analyses [24].

Case id	Timestamp	Activity	tivity Transaction type			
5302	23/08/2021	Deviaturation	Stant	Receptionist		
	08:51:33	Registration	Start	Monica		
5295	23/08/2021	CT acon available	Complete	Radiologist		
	08:53:12	C1 scan available	Complete	David		
5303	23/08/2021	Deviatoration	Charact	Receptionist		
	08:54:36	Registration	Start	Michael		
5302	23/08/2021	Deviaturation	Complete	Receptionist		
	08:55:01	Registration	Complete	Monica		
5301	23/08/2021	EEC toot	Complete	Lab technician		
	08:58:19	EEG test	Complete	Jennifer		
5302	23/08/2021	Consultation	Stant	Neurologist		
	09:02:46	Consultation	Start	William		
5303	23/08/2021	Derictrotion	Complete	Receptionist		
	09:03:25	Registration	Complete	Michael		
5301	23/08/2021	Consultation	Stort	Neurologist		
	09:07:59	Constitution	Start	Amy		
5292	23/08/2021	Uning tost	Complete	Nurse		
	09:08:12	Office test	Complete	Robert		
5303	23/08/2021	EEC toot	Stant	Lab technician		
	09:10:53	EEG test	Start	Jennifer		
5287	23/08/2021	Diashanna	Stant	Neurologist		
	09:14:49	Discharge	Staft	Lisa		

Table 1: Example of event log (based on [4])



Figure 1: Positioning process mining in healthcare (based on [2, 4, 15]).

2.2. Existing literature reviews on process mining in healthcare

Over the last years, several literature reviews on process mining in healthcare have been published. In total, ten recent literature reviews were identified. A primary distinction can be made between literature reviews focusing on a particular healthcare subdomain (e.g. a particular set of medical conditions) versus reviews handling process mining in healthcare in general. Four recent reviews consider process mining in a healthcare subdomain. Kurniati et al. [19] focus on process mining in an oncology setting, with their review mainly centering around the distribution of literature over process mining types, perspectives, and tools. Next, Kusuma et al. [20] give a review of the state of process mining in cardiology, looking into process mining types, perspectives, tools, methods, and opportunities. The review of Williams et al. [21] builds upon the review of Rojas et al. [15], using the reviewed paper set of Rojas et al. [15] but only focusing on the subdomain of primary care. In their review, they discuss the application of process mining in this specific subdomain mainly by looking at the geographical locations of the current research, used data sets and challenges. Next, Farid et al. [22] used similar review dimensions as Williams et al. [21] but applied these to the subdomain of frail elderly care [25].

While the aforementioned four reviews focus on process mining in a specific healthcare subdomain, six literature review papers consider process mining in healthcare in general. Ghasemi and Amyot [16] focused on mapping the evolution in the number of published papers, as well as studying existing reviews on process mining in healthcare. Next, Rojas et al. [15] provide a thorough review of the state of the process mining in the healthcare domain. In their exclusion criteria the authors explicitly state papers regarding Clinical Pathways (CPs) are not included in the research. The review of Batista and Solanas [17] classifies the literature according to nine different dimensions, of which several are in line with Kurniati et al. [19]. In addition, they also have a look at the relevant medical fields, medical facilities, data, and data pre-processing techniques. Further, Erdogan and Tarhan [18] systematically map publications on process mining in healthcare according to several dimensions in line with previous reviews, and highlight some trends and demographics regarding the publications. Rule et al. [3] specifically reviewed papers on the use of electronic health records audit logs. Consistent with this different review goal, and in contrast to the aforementioned reviews, Rule et al. [3] only consider PubMed for the identification of papers. Lastly, the most recent review of Dallagassa et al. [11] provides an overview of the history of process mining in healthcare, describing some important milestones and main contributions to the domain. Furthermore, they discuss the considered healthcare environments, used process mining types and applied algorithms of the reviewed papers.

To position the contribution of our paper, Table 2 positions our review with respect to the aforementioned review papers. The literature reviews differ in terms of the dimensions which are considered to classify literature. Dimensions used by several reviews include the process types [15, 17, 19, 20, 22] process mining types [11, 17–20], and process mining perspectives [15, 17, 19, 20] considered, as well as the process mining algorithms used [11, 15– 18, 20]. While other papers discuss which algorithms are used in the papers, we look deeper into it and distinguish papers that develop algorithms, papers that apply algorithms and combinations of these two.

Our review clearly distinguishes itself by considering three dimensions which received no or very limited attention in existing reviews. Firstly, we classify literature regarding the process mining project stages of Aguirre et al. [23] that are considered, a dimension which none of the prior reviews considered. Secondly, although several papers argue about the importance of interdisciplinary teams, close collaborations and the involvement of clinical experts [4, 26] only two of the prior reviews briefly highlight the need for domain expertise [20, 22]. However, it is not used as a review dimension. Therefore, this research explicitly classifies literature with respect to the involvement of domain experts in several stages of a project (i.e. problem identification, data extraction, data preparation, interactive analysis and validation of gathered insights) Finally, we discuss the use of KPIs, which only Batista and Solanas [17] discuss. However, Batista and Solanas [17] only mention the increased interest in the use of KPIs, but they do not use it as a review dimension. Hence, we incorporate the KPIs considered as an explicit review dimension.

Besides the aforementioned unique review dimensions, our review also elaborates on time trends in the research fields. Six existing reviews consider time trends [3, 11, 16, 19, 20] but not all with the same level of detail. The reviews of Ghasemi et al. [16], Kurniati et al. [19] and Kusuma et al. [20] only discuss the number of publications over time very briefly by showing a bar chart over the years. Rule et al. [3] does the same but adds publications mentioning duration to the chart. Further, Erdogan and Tarhan [18] included, next to the bar chart, also a concise timeline with the number of publications per process mining type. Lastly, Dallagassa et al. [11] show a timeline with important milestones for the domain. Given the explicit focus on time trends within the review dimensions, our review adds a unique view on the trends and patterns over time in the process mining in healthcare domain.

From the previous, it follows that our systematic literature review adds new perspectives compared to existing reviews. Besides providing the most recent overview of literature and the extensive set of papers considered, we classify literature according to several dimensions that were not adequately covered by prior reviews. In particular, we explicitly classify literature according to the process mining project stages, the involvement of domain expertise, as well as the KPIs considered. Moreover, we highlight the evolution of the research domain by considering time trends within several review dimensions.

	Ghasemi and Amyot [16]	Kurniati et al. [19]	Rojas et al. [15]	Batista and Solanas [17]	Erdogan and Tarhan [18]	Kusuma et al. [20]	Williams et al. [21]	Farid et al. [22]	Rule et al. [3]	Dallagassa et al. [11]	This paper
Publication year	2016	2016	2016	2018	2018	2018	2018	2019	2020	2021	2021
Review scope	General	Oncology	General	General	General	Cardiology	Primary care	Frail elderly care	General	General	General
Review period	Until 13/05/16	Not reported	Until 08/02/16	Not reported	2005-2017	January 1998- 02/06/17	Until 05/10/17	1998- October 2018	Until July 2019	2002- December 2019	Until January 2021
Number of reviewed papers	11	37	74	55	172	32	7	8	86	270	263
Review dimensions											
Process type	0	•	•	•	0	•	0	•	0	0	•
Process mining types	0	•	0	•	•	•	0	0	0	•	•
Process mining perspectives	0	•	•	•	0	•	0	0	0	0	•
Process mining algorithms used	•	0	•	•	•	•	0	0	0	•	•
Process mining project stages	0	0	0	0	0	0	0	0	0	0	•
Involvement of domain expertise	0	0	0	0	0	●	0	•	0	0	•
KPI	0	0	0	•	0	0	0	0	0	0	•
Time trends											
Number of publications	•	•	0	0	•	•	0	0	•	•	•
Review dimensions	0	0	0	0	D	0	0	0	•	0	•

Table 2: Comparison of this review to prior domain literature reviews. \bullet Yes, included as a review dimension in the review. \bullet Briefly mentioned, but not included as a review dimension. \bigcirc No, not mentioned in the review.

3. Methodology

This section describes the used methodology. In particular, Section 3.1 introduces the review questions, Section 3.2 outlines the review dimensions and Section 3.3 describes the search strategy.

3.1. Review questions

To provide a structured overview of published research on process mining in healthcare, our review is centered around the following review questions:

- **Review question 1**: What is the process mining focus of the published papers on process mining in healthcare?
- Review question 2: Which process mining project stages are discussed in published papers on process mining in healthcare?
- Review question 3: How are domain experts involved in the process mining in healthcare studies reported in?
- Review question 4: Which key performance indicators (KPI) are used in published papers on process mining in healthcare?
- Review question 5: How did process mining in healthcare evolve over time as a research field in terms of the review dimensions highlighted in review questions 2, 3 and 4?

It should be noted that review question 1 is consistent with previous reviews on process mining in healthcare. However, review questions 2 to 5 lead to new perspectives on the literature in the domain. Review question 5 will be considered orthogonally to questions 2, 3 and 4, i.e. for each of these review dimensions, the time perspective will also be considered. The review questions will be contextualized in Section 3.2.

3.2. Review dimensions

This subsection outlines all review dimensions that will be used in more detail.

3.2.1. General descriptives

To structure the papers during the review process, some general descriptives are collected, i.e. the year of publication and whether the paper is a journal paper or a conference proceeding (as well as the specific journal or conference). Moreover, papers are classified as one of the following four types:

- Literature review: the paper reviews prior literature.
- Conceptual contribution: the paper presents a conceptual contribution which does not result in an executable artefact. However, it is possible that it lays the foundations of a particular method, but the method is not operationalized, implemented nor applied in a real-life setting.
- Method design and implementation: the paper designs a method, which is also implemented to generate an executable artefact (and potentially apply it to a synthetic example).
- Method application: the paper applies a method within a real-life context. This method is either an existing method or in combination with "Method design and implementation".

3.2.2. Process mining focus

This review dimension consists of five subdimensions, namely (i) type of process, (ii) process mining type, (iii) process mining perspective, (iv) algorithm development or application and (v) techniques with which process mining is combined.

The first subdimension classifies the *type of process* based on the distinction by Lenz et al. [1] between clinical processes on the one hand and administrative or organizational processes on the other hand. Clinical processes cover medical or medical treatment processes, these are linked to medical decision making (e.g. diagnostic procedures) and medical guidelines. Administrative or organizational processes link medical staff with other units of a healthcare organization. It is possible that a paper discusses both process types.

The second subdimension describes the *type of process mining* used in the paper, based on the classification of van der Aalst [2]. The three types are discovery, conformance and enhancement. Process discovery means that a model is retrieved from an event log. Conformance checks or compares whether an existing model, either hand-made or discovered, matches with reality as observed in an event log. During enhancement, an existing model can be extended or improved. It is possible a paper discusses multiple process mining types.

The next subdimension covers the considered *process mining perspectives* defined by van der Aalst [2]. The four perspectives are control-flow, organizational, case and time. Discussing the control-flow perspective in a paper implies the authors look at the sequence of the activities. Looking at the

organizational perspective means examining the behavior of resources in the process, e.g. using a social network. The case perspective looks at properties of cases, e.g. several types of patients that are compared based on a specific property. When the time perspective is discussed in a paper, the authors look at the timing and frequency of the events. It is possible that a paper discusses multiple process mining perspectives.

The fourth subdimension checks whether the paper focuses on *algorithm development* or *algorithm application*. It is possible that a paper discusses both as the authors can first develop the algorithm and then apply it.

The last subdimension looks into *techniques with which process mining is combined* in the paper. It is useful to gain insight into current techniques from other domains such as data mining with which process mining is combined.

3.2.3. Process mining project stages

There are several methods that describe how to execute a process mining project, such as the L* life-cycle [2] and PM2 methodology [27]. We want to gain insight into the extent to which existing process mining in healthcare research systematically goes through the different stages of a process mining project. For the classification, we opt for the framework of process mining project stages of Aguirre et al. [23], which consists of four stages. The first stage is the *project definition*, where the business process and problems need to be introduced and it should be specified how process mining can help. In the second stage, *data preparation*, the data should be located in the systems, extracted and assessed in terms of data quality. The third stage, *process analysis*, covers the actual application of the process mining techniques (discovery, conformance, enhancement). Lastly, during *process* *redesign*, specific improvements to the process are proposed. Note that this stage is only marked to be present in a paper when the paper reports on implementable measures. Merely mentioning that the analysis could constitute as a basis for process redesign is not sufficient.

3.2.4. Involvement of domain expertise

Several papers argue about the importance of interdisciplinary teams, close collaborations and the involvement of clinical experts [4, 26]. There are numerous stages in which a domain expert can be involved in a process mining project. It is important to consider in which stages domain experts are consulted and involved. In this review, we distinguish five stages in which they can potentially be involved:

- **Problem identification**: the domain expert assists to set objectives and specific questions that need to be answered by process mining.
- **Data extraction**: the domain expert is involved in extracting the data from the system, e.g. by granting access to data.
- Data preparation: the domain expert is involved in preparing the data, e.g. by assisting in data quality assessment and data cleaning
- Interactive analysis: the domain expert is systematically involved during the actual execution of the analysis.
- Validation of gathered insights: the domain expert evaluates the final outcomes of the process mining analysis.

Only when the involvement of an expert during a particular stage is explicitly mentioned in the paper, it is marked accordingly in the review. These stages can be linked to the process mining project stages of Aguirre et al. [23] introduced in Section 3.2.3. Firstly, *problem identification* is part of the process definition stage. Secondly, *data extraction* and *data preparation* can be linked to the data preparation stage. Finally, *interactive analysis* and the *validation of gathered insights* can be connected to the process analysis stage. To classify the involvement of domain experts, the five stages outlined above are purposefully used as they enabled a more fine-grained analysis compared to the stages of Aguirre et al. [23]. Note that the redesign stage in Aguirre et al. [23] is not considered given the focus on the actual analysis of process data.

3.2.5. Key Performance Indicators under consideration

A KPI reflects a specific target that the authors focus on when conducting an analysis. A wide variety of KPIs can be considered in a healthcare context. In our review, a basic distinction between four categories will be made: clinical, financial, time-related and resource-related KPIs. The latter two categories can be considered as subcategories of the broader category of operational KPIs. A clinical KPI is for example a specific type of measurement regarding the medical condition of a patient, while a financial KPI is for example the cost per patient. A typical example of a time-related KPI is the waiting time of a patient at the emergency department and an example of a resource-related KPI is the bed occupancy of the intensive care unit.

3.2.6. Time dimension

Orthogonal to these review dimensions, we can study their evolution over time to gain insights in the evolution of the research field. For each dimension, the number of papers that consider a certain stage or KPI are reported, providing an overview of the absolute number of publications per year in a chart. Besides, as not each year contains the same number of papers, it is useful to provide an overview of the relative number of papers as well. The relative numbers will reflect the fraction of the papers published in a particular year that, e.g., discuss a process mining project stage or use a KPI.

3.3. Search strategy

In this section, the step-by-step search strategy is explained. Figure 2 shows a summary of the search strategy. The search includes papers up to and including January 2021. The collected data and notes were stored in a spreadsheet, using the listed review dimensions as columns.

3.3.1. Scoping search

To establish and finetune the search strategy and search terms, scoping searches were conducted. The final goal of this stage is to find the search query that will be used throughout the paper search process for all the listed databases.

During scoping searches, three databases are initially used, namely PubMed, Web of Science and IEEE Xplore. PubMed is chosen as a first database to start from as the topic of the paper is related to the healthcare domain, followed by Web of Science and IEEE Xplore. The PubMed search settings were set on [All Fields].

During this stage, different search terms are tested, also taking into account the search terms of existing literature reviews. Moreover, several deci-



Figure 2: Search strategy.

sions concerning which words to include or exclude from the query are made along the way. As process mining in healthcare requires multidisciplinary efforts, it is important that all domains and their contributions are represented in the search terms. For example, in the (bio)medical domain, the term "process mining" may be less explicitly mentioned.

The scoping searches highlighted that including the terms "workflow mining" and "healthcare" in the search query have no influence on the number of results on PubMed, but searching Web of Science shows the relevance of including these terms in the search query. "Process analysis" and "pathway analysis" were excluded from the query as it was too broad and too many irrelevant results were found in all three databases. Also, the term "pathway mining" was excluded as it resulted in many irrelevant results on PubMed and Web of Science. Next, the term "Electronic Health Record" was excluded as the additional papers on PubMed, Web of Science and IEEE Xplore were not in line with process mining topic of this review. Lastly, the terms "healthcare information systems" OR "hospital information systems" were too broad and resulted into many irrelevant results on all three databases.

Based on the scoping searches, the following final search query is obtained: ("process mining" OR "workflow mining" OR "process discovery" OR "audit log" OR "event log") AND ("healthcare" OR "health" OR "care" OR "clinical" OR "hospital" OR "medical" OR "patient")

3.3.2. Initial paper identification

Using the search query in PubMed, Web of Science and IEEE Xplore resulted in 1125 identified articles for the review. Afterwards, two additional databases are taken into consideration: Scopus and Google Scholar. These are included to cross-check the primary three databases. Given the large number of search results in the Scopus and Google Scholar databases, e.g. Google Scholar showed more than 17.000 results, the first 500 search results were considered for both databases. For Google Scholar the settings used incognito mode, "Search English results only", excluding patents and citations. This additional search resulted in 137 extra articles for the review.

After the database searches, duplicate screening took place, which reduced the number of articles to be screened in the next step to 948.

3.3.3. Title and abstract screening

During this preliminary selection, only the titles of the papers are screened. The following **exclusion criteria** are considered during title screening:

- Papers on purely clinical parameters (e.g. medical procedures, treatment, clinical trials, etc.)
- Papers focusing on the legal or privacy implications of personal data processing
- Papers on purely managerial aspects (e.g. organizational transformation, reorganization, implementation of new systems, etc.)

Afterwards, the titles and abstracts of the remaining 618 papers are screened. To this end, the following inclusion and exclusion criteria are used: The **inclusion criteria** are:

• The paper's primary focus is on process mining within a healthcare setting (without requiring that the term "process mining" is explicitly mentioned)

• The papers should be published in a peer-reviewed scientific journal or peer-reviewed conference proceedings

The exclusion criteria are:

- Papers about setting up or implementing healthcare information systems
- Papers in which the process orientation is absent
- Papers in which a relevant problem within the healthcare domain is missing (e.g. other domains than healthcare are not relevant for this review)
- Papers not written in English

3.3.4. Full text screening

During this step, the remaining 331 full-text papers are accessed for eligibility and, if needed, are excluded with reasons (i.e. double check of the inclusion and exclusion criteria mentioned in Section 3.3.3 based on full text). The following **additional exclusion criteria** are taken into consideration:

- Full text of the paper not available
- The previous conference paper of a published article can be excluded
- Posters, one-page papers, executive summaries and abstracts
- Commentaries

At the end of the second screening, the final 263 papers for the review were selected.

4. Results

This section classifies the 263 papers included in the final paper selection according to several review dimensions. In particular, Section 4.1 provides some general descriptives, Section 4.2 examines the process mining focus, Section 4.3 discusses the process mining project stages, Section 4.4 explores the involvement of domain expertise and Section 4.5 covers the use of KPIs. Orthogonal to the review dimensions, we discuss the time dimension, which highlights the evolution of the research domain over time.

4.1. General descriptives

The 263 publications incorporated in this review include both scientific journal papers and conference proceedings: 121 journal papers (46%) have been included in the selection and 142 conference papers (54%). The most frequently recurring scientific journals are the International Journal of Environmental Research and Public Health (14 papers; 5,3%), Journal of Biomedical Informatics (11 papers; 4,2%), Studies in Health Technology and Informatics (8 papers; 3%).

As mentioned in Section 3.2.1, a distinction is made between various types of papers: literature reviews, conceptual papers, papers that design and implement a method, and papers that apply a method. Most reviewed papers (110 papers; 41,8%) combine the design and implementation of a method with its application to, e.g. a case study. 25,5% (67 papers) only covered the application of an existing method. 18,6% (49 papers) described just the design and implementation of a method, sometimes accompanied by a brief synthetic example, but without a full-fledged detailed application in a real-life context. Lastly, 10,3% (27 papers) were conceptual papers and 3,8% (10 papers) were literature reviews.

Figure 3 visualizes the evolution in the number of publications over time. Especially since 2013, there has been a consistent rise in the number of publications on process mining in healthcare, demonstrating the gradual growth of the research domain.



Figure 3: Used publications for systematic literature review.

4.2. Process mining focus

This section classifies papers according to their process mining focus, where we distinguish several subdimensions. Firstly, we consider the *type* of process considered, making a distinction between clinical processes and organizational processes [1]. Clinical processes are the process type most discussed in the reviewed papers (168 papers; 63,9%), followed by organizational processes (20 papers; 7,6%) or a combination of both (40 papers; 15,2%). Examples of reviewed clinical processes are linked to treatment processes [27–33] for medical conditions such as acute ischemic stroke [28], sepsis [29], cancer [32, 34, 35], and chronic diseases such as arterial hypertension [30] and unstable angina [33]. Organizational processes include billing processes [36–38] and reimbursement processes [39]. A combination of both processes can be found, for example, in Naeem et al. [40] who on the one hand describe a clinical treatment process of hepatitis patients and on the other hand create a social network model to study the interaction between resources. Alvarez et al. [41] also consider both clinical and organizational processes by analyzing both clinical emergency room processes as well as role-resource interaction models. In 13,3% of the papers (35 papers), no specific type of process was considered as it constituted a conceptual paper or a literature review.

Secondly, regarding the process mining type, most papers examine, either in isolation or combined with the other types, discovery (213 papers, 81%), followed by conformance (82 papers, 31,2%), then enhancement (39 papers, 14,8%). Conformance and enhancement are mostly discussed in combination with discovery, respectively 27% (71 papers) for conformance and discovery, and 13,7% (37 papers) for enhancement and discovery. Examples of discovery include the discovery of process models from event logs taking into account role interaction between different resources [41] or to understand the emergency room discharge and triage process [42]. Next, examples of conformance checking are checking the compliance of real-life process behavior with clinical guidelines [43–45] or comparing a discovered model and reality [46– 49]. Enhancement includes papers focusing on the improvement or repair of an existing model e.g. [46, 50, 51], as well as papers related to prediction e.g. [52–54].

Thirdly, the process mining perspectives control-flow, time, organizational and case are examined [2]. Control-flow is discussed the most (179 papers; 68,1%, in isolation or combined with other perspectives), followed by the time (71 papers; 27%), case (27 papers; 10,3%) and the organizational (24 papers; 9,1%) perspective. Time is also mostly combined with the controlflow perspective (58 papers, 22,1%) and with the case perspective as well (25 papers; 9,5%). The organizational perspective is combined with the control-flow perspective in 19 papers (7,2%). An example of the controlflow perspective is the paper of Lamine et al. [55] who discover the controlflow of incoming emergency call regulation process using the fuzzy miner from an event log. Next, the time perspective can be found for example in the paper of Partington et al. [56], who compute various time measures such as the waiting time and length of stay to find possible bottlenecks in the hospital processes and opportunities for improvement. An example of a paper focusing on the organizational perspective is Lismont et al. [57] who use the social network miner to visualize the discovered handover of the work between a general practitioner and specialists. Similarly, Pika et al. [58] apply the social network miner to three publicly available healthcare datasets to discover a social network representing the resources. The case perspective, for example, covers papers comparing different groups of clusters of patients. Zhou et al. [59] compare high-risk and low-risk patients while generating a process model of an outpatient clinic and looking into its performance.

Fourthly, a distinction can be made between papers that develop new algorithms and papers that apply existing algorithms in an innovative context. Algorithm application (156 papers; 59,3%) occurs more frequently than algorithm development (25 papers; 9,5%), or a combination of the two (23 papers; 8,7%). A combination of the two means that the algorithms are developed in the paper and immediately applied, potentially in combination with existing algorithms. In 22,1% of the cases (58 papers), this distinction was not relevant as these papers were, for example, conceptual papers or literature reviews. Popular algorithms that are applied include heuristics miner [60–65], fuzzy miner [66–68], and inductive miner [58, 69, 70].

Finally, it is assessed whether process mining is *combined with other tech*niques. Process mining algorithms are quite often combined with techniques from other domains such as clustering. For example, Prokofyeva et al. [71] use hard and fuzzy clustering to distinguish patient groups within the context of a clinical pathway. Similarly, Najjar et al. [72] cluster patient treatment pathways into homogeneous clusters for further analyses. Toledo et al. [73] cluster groups of patients with similar characteristics, while Durojaiye et al. [74] and Yang et al. [67] also create patient cohorts using clustering to compare them at a later stage. In recent years, process mining is increasingly combined with machine learning techniques, e.g. Metsker et al. [7] and Mesabbah et al. [75] use machine learning methods as a prediction tool.

4.3. Process mining project stages

This section classifies the papers based on the project mining project stages. A full overview of the papers classified under the process mining project stages can be found in Appendix A. The first stage, *project definition*, was discussed in 52,5% of the papers (138 papers). These papers mentioned an objective or problem to be solved by process mining. For example, Remy et al. [76] introduce specific questions to be solved by process mining within the context of the treatment process of low back pain. For instance: at which point in the treatment process are opioids applied? Similarly, Kurniati et al. [77] have three specific questions to be answered during the process mining project on the assessment of data quality issues. For instance: can the MIMIC-III database be used to better understand data quality issues for process mining in healthcare?

The second stage, *data preparation*, was outlined in 55,5% of the studies (146 papers). In this stage, 22,1% of all reviewed papers (58 papers) mentioned data pre-processing as a preparatory stage, more specifically mentioning data filtering (12,9%; 34 papers; e.g. [35, 50, 78–81]), data cleaning (9,1%; 24 papers; e.g. [82–86]), or data conversion (5,7%; 15 papers; e.g. [37, 64, 66, 87, 88]).

The process analysis stage, the third stage in a process mining project, was discussed in 78,7% of the publications (207 papers). This stage was not reported in literature reviews, conceptual papers and papers covering the design and implementation of a method (e.g. using a synthetic example), as they do not discuss a process mining project.

Lastly, the *process redesign* stage was only reported in 5,3% of the papers (14 papers). For example, Stefanini et al. [62] focuses on the discovery of patient flows in a lung cancer unit. The obtained process models were reviewed and redesigned together with the medical experts.

When considering the time dimension, Figure 4 visualizes the evolution

in the absolute number of publications reporting on various process mining project stages over time. On the other hand, Figure 5 shows an overview of the publications relative per year. When looking at these numbers several observations can be made, although it should be noted that the relative values for the years 2005 to 2012, as well as 2021, must be interpreted in a nuanced way given the small publication numbers. Firstly, over time, there has been a systematic focus on process analysis, which is expected as this is the core of process mining papers, with the exception of literature studies and conceptual papers. Secondly, in recent years there has been growing attention for project definition and data preparation. Lastly, the attention to process redesign is limited and to date no strong trend can be observed.



Figure 4: Process mining project stages absolute per year.

4.4. Involvement of domain expertise

This section describes the involvement of domain experts in different stages of process mining projects. As outlined in Section 3.2.4, their ex-



Figure 5: Process mining project stages relative per year.

pertise can be included during problem identification, data extraction, data preparation, when conducting an interactive analysis, and when validating the gathered insights. A full classification of the papers with regards to the involvement of domain experts can be found in Appendix B.

Domain experts are the most frequently involved to validate findings during a process mining study. In total 23,2% (61 papers) explicitly report that they have collaborated with domain experts in this stage. For example, Xu et al. [6] performed conformance checking on ischemic stroke patient data and presented their results to neurologists. In their turn, Canjels et al. [51] presented the results of their analysis of the arthrosis care process to their expert team, consisting of three orthopedic specialists and a process analytics expert, and discussed the outcomes.

While the involvement of domain experts for validation purposes occurs towards the end of a process mining project, 14,4% of the papers (38 papers) reported that the domain expert actively participated in an *interactive* analysis. For example, Remy et al. [76] reported on several analysis iterations with domain experts, which were also actively kept in the loop during subsequent revisions of the analysis outcomes.

Domain experts were involved for 13,3% (35 papers) during *data extraction*. Several papers [27, 39, 70, 75, 89, 90] mention that the hospital provided them the dataset or granted them access to the data. Rebuge et al. [9] discussed with the data team coordinator how to explore the data in the specific database they received access to.

In 12,5% of the papers (33 papers), domain experts were reported to be actively involved during the *problem identification* of a project. Several papers [29, 39, 91–94] conducted interviews with experts and/or staff to have a better understanding of the processes and work environment. For instance: Gerhardt et al. [39] interviewed an operations manager so they could understand the reimbursement process and the problems linked to it.

Data preparation was guided by domain experts in a total of 11,4% (30 papers). For example, for their research on the optimal pathway discovery using sepsis hospital admission data, De Oliveira et al. [95] mention to exclude pediatric sepsis pathway in consultation with their clinical experts. Remy et al. [76] discussed the reliability of the data with the domain experts, but mentions that data quality was not yet considered, whereas Johnson et al. [96] describes a clinical inspection of the data quality of the electronic health records with domain experts. Benevento et al. [97] highlights that the medical staff helped with the preparation of the event logs to study lung cancer treatment.

Ten publications (3,8%) involved a domain expert *in each stage*. A few recent papers specifically mention the research was done within an interdisciplinary team. Kusuma et al. [98] worked with a team including a clinician, epidemiologist, and computer scientists, while the team of Pereira et al. [99] consisted of people with different backgrounds in healthcare and IT. Xu et al. [100], Aguirre et al. [101] and Durojaiye et al. [94] worked together with one or more medical experts in the team. The team of Montani et al. [63, 102] included an experienced physician in the field as a co-author but also a specific expert for the problem identification. Also, Kurniati et al. [103] had an oncologist in their team together with computer scientists. Moreover, during the stages of data preparation, interactive analysis and validation additional clinical experts were involved in the discussion. In Remy et al. [76] and Rojas et al. [42], the domain expert was not a part of the operational team but was interviewed or consulted for each stage.

When considering the evolution over time of this dimension Figure 6 visualizes the evolution in the absolute number of publications involving domain experts and Figure 7 shows an overview of the publications relative per year. When looking at these numbers several observations can be made, although it should be noted that the relative values between 2005 and 2012, as well as 2021, should be viewed with caution given the small numbers of publication for these years. Firstly, domain experts have been involved during problem identification, data extraction and interactive analysis since 2012. In 2013 domain experts were involved for the data preparation stage for the first time. Secondly, as can be seen on Figure 6, the last three years show an increase in the involvement of domain expertise. However, the relative numbers do not
show a consistent increase in attention to domain expert involvement in recent years, although the number of publications within the research domain has increased sharply since 2013. In the preceding period, between 2013 and 2015, there were considerably fewer publications in absolute numbers, but relatively more attention was paid to involving domain experts, in particular for validating insights. Lastly, only the involvement of domain experts in the validation of insights has seen a steady increase since 2016, although in 2020 this still represents only 30% of the papers published in that year.



Figure 6: Involvement of domain experts absolute per year.

4.5. Key Performance Indicators under consideration

This section classifies literature according to the KPIs which are used within the context of a process mining analysis. As mentioned in Section 3.2.5, a distinction is made between clinical, financial, time-related, and



Figure 7: Involvement of domain expert relative per year.

resource-related. A full list of the papers classified under the KPIs can be found in Appendix C.

A time-related KPI was used in isolation in 52 papers (19,8%) and combined with other KPIs in 29 papers (11%). Examples of time-related KPIs include length-of-stay e.g. [54, 104–107], waiting time e.g. [108–110], doorto-doctor time e.g. [52, 111], throughput time or the time between two tasks e.g. [47, 65].

A clinical KPI was used by itself in 27 papers (10,3%) and combined with other KPIs in 23 papers (8,7%). Examples of clinical KPIs can be found in the paper of de Vries et al. [112] which emphasizes checking lactate measurement, blood cultures, antibiotics administration and volume expansion for sepsis treatment. Also, the paper of Lu et al. [113] focuses on specific vital signs and physiological variables of cancer patients. A financial KPI was used in 3 papers in isolation (1,1%) and considered in combination in 6 papers (2,3%). For example, Spoel et al. [114] describe how Dutch hospitals will apply a new system for patient billing costs to insurance companies and want to increase the transparency of financial information to the patients. In that respect, their paper focuses on the prediction of the costs of the provided care. Another example of financial KPI is the paper of Phan et al. [66] who compare obese and non-obese patient groups to compare the costs per patient. Also, the paper of Dahlin et al. [115] examines the relationship between breast cancer patient pathways and patient costs.

Lastly, a resource-related KPI was never exclusive, but was always combined with other KPIs in 7 papers (2,7%). For example, Benevento et al. [108] look at the number of physicians and nurses inside the emergency department per shift. Moreover, Elhadjamor et al. [84] jointly consider the staff availability of (para)medical staff and the waiting time before sorting, as well as other combinations of KPIs within the emergency room context. Aguirre et al. [101] look into surgery processes for a specific healthcare network with five facilities and discuss several indicators for possible process improvements amongst which operational capacity (e.g. number of surgeries in one room).

Only one paper combines *all four types of KPIs*: Cho et al. [52] propose a framework for emergency room process performance indicators, focusing on time, cost, quality, and flexibility. Examples of these indicators are length-of-stay, cycle time of a clinical activity, initial response time after arrival at emergency room, total cost for patient, workload of resources, and accuracy of medical triage for patients.

For 149 papers (56,7%), no specific KPI was taken into consideration.

This can partly be attributed to the presence of 37 literature reviews and conceptual papers (14,1%). However, many other papers (112 papers; 42,6%) for example [105–107] focused purely on providing insights into the process, rather than studying the process from the perspective of one or more specific KPIs. For example, Montani et al. [116] focus on developing a framework for knowledge-based abstraction of event log traces, these traces are the input to semantic process mining. The framework is applied to stroke care.

Considering the evolution over time of this dimension Figure 8 visualizes the evolution in the absolute number of publications that consider a KPI, and Figure 9 shows an overview of the publications relative per year. While looking at the figures, some observations can be made. Firstly, the number of papers that use targeted KPIs to guide the analysis has been increasing, especially since 2016. Before 2016 the numbers are very small. Secondly, relatively speaking, the use of time-related KPIs is fairly constant over time, provided slight fluctuations are taken into account. No clear trend can be observed with regard to the relative importance of clinical KPIs. The year 2020 shows a huge increase in the use of clinical KPIs, so the future will show whether this trend will continue.



Figure 8: Key Performance Indicators absolute per year.



Figure 9: Key Performance Indicators relative per year.

5. Discussion

Section 4 classified 263 papers on process mining in healthcare according to the review dimensions outlined in the methodology. This section discusses the key observations which shed a light on the evolution of the research domain, as well as providing recommendations for its future development.

In general, alongside process mining in general [117], process mining in healthcare has significantly grown as a research domain. Since 2013, the number of published papers has gradually increased. The majority of process mining research in the healthcare field focuses on analyzing clinical processes, i.e. processes related to the medical and medical treatment processes [1]. Consistent with the findings of prior literature reviews, our results show a predominant focus of research efforts on the discovery of process models from an event log, mostly targeting the identification of the order of activities in a healthcare process (i.e. the control-flow).

Regarding the process mining project stages, our results highlight three key observations. Firstly, only 52,5% of the papers (138 papers) explicitly mention an objective or specific research question. This implies that an important part of the body of literature does not start from a specific healthcare question or problem, but rather showcase the potential of a particular process mining method. While demonstrating the potential of a technique might be required to raise awareness in its early days, its adoption in the long run will depend upon the technique's ability to solve relevant problems. In order to generate real-life impact in the healthcare domain, it is critical that process mining solves real-life problems experienced by clinicians and other healthcare professionals. Secondly, only 22,1% of the reviewed papers (58 papers) explicitly report on the data preparation activities. Given the potential impact of data preparation activities such as data filtering or data cleaning on the trustworthiness of process mining outcomes, transparency on this matter is important. Transparency enables the reader to put the reported results into perspective, which is important when studying processes with far-reaching real-life implications such as medical treatment processes. Thirdly, process redesign is only elaborated in a small fraction of the published process mining papers (5,3%; 14 papers). This indicates that most contributions do not have the time to elaborate on this stage and focus on the analysis stage targeted at deriving insights in a healthcare process. While these insights are likely to lead to a better understanding of the process, it should be noted that the actual added-value for clinicians and healthcare practitioners is generated when this understanding also leads to process improvement.

With respect to the *involvement of domain experts* throughout the project, our review highlights that domain experts are the most frequently involved for the validation of insights. While this marks the most frequent stage in which domain experts are involved, it still is only reported in about a quarter of the reviewed papers (23,2%; 61 papers). This shows that, if involved altogether, the expertise of clinicians and other healthcare professionals are mainly used to assess the meaningfulness of the generated outcomes. Less than 15% of the reviewed papers report that domain experts are involved in other phases such as problem identification, data extraction and data preparation. Only 10 papers (3,8%) report consultations with domain experts throughout the entire project. This could be considered as rather limited in the light of the complexity of the healthcare domain, the knowledge-intensive character of healthcare processes and the widespread presence of data quality issues [4, 8].

Related to the KPIs considered in the analysis, the literature classification highlights that a 43,3% of the papers (114 papers) considers a specific KPI when studying a healthcare process using process mining. Centering the analysis around a particular KPI gives it a particular direction and focus. Moreover, using relevant KPIs also enables synchronizing process mining initiatives with the ambitions of a department or healthcare organization, which can also be beneficial for the adoption of process mining in healthcare. When a KPI is explicitly considered, time-related KPIs are considered the most often (81 papers; 30,8%), followed by clinical KPIs (50 papers; 19%). Combinations of KPIs from different categories, e.g. time-related and clinical KPIs, are rarely used (7 papers; 2,7%), but are promising as they enable process mining analyses to explicitly consider trade-offs between KPIs. For instance, particular behavior in the process might be highly inefficient from an operational point of view (as reflected in a time-related KPI), but might generate significant added value from a clinical perspective (as reflected in a clinical KPI).

The insights from this literature review can also be leveraged to provide recommendations for the future development of process mining in healthcare as a research field. The following five considerations are of particular interest given the observations from our literature review:

• Future research should focus on tackling real-life healthcare problems, i.e. have a demand-driven character. Targeting issues which are relevant for clinicians and other healthcare professionals will increase the impact of process mining and, hence, the likelihood of its systematic adoption in daily healthcare practice. Also closely involving these healthcare professionals during the project will stimulate the focus of the process mining project.

- There is a need for more research on the translation of the outcomes of process mining techniques to actionable process improvement ideas in healthcare. Currently, research often limits itself to the analysis stage, while true value is only generated for healthcare organizations when analysis results can be converted in specific actions leading to process improvement.
- It is recommended to closely involve domain experts throughout the process mining project and not only for the validation of the generated insights. In a healthcare setting, their expertise is typically indispensable to generate valuable insights. Even though the availability of domain experts is often highly constrained, regular interaction enables them to share knowledge and indicate their information needs. In this way, the analysis outcomes will better fit their expectations, which will enhance their commitment within the project.
- Future work could focus on process mining analyses which simultaneously consider various KPIs, e.g. a combination of a time-related KPI and a clinical KPI. This would provide clinicians and other healthcare professionals with explicit insights in the trade-offs between various KPIs, resulting in richer and more balanced insights than analyses targeting a single KPI.

• There is a need for reporting guidelines when a process mining in healthcare study is presented. The literature review has shown that limited details are typically provided to the reader regarding essential components of a process mining analysis such as data preparation and the way in which domain experts were involved. Reporting guidelines should ensure that adequate information on these matters is provided. Besides enhancing transparency, this would also enable rigor assessment of research conducted in the domain.

The contributions of this review need to be reflected against its limitations. Firstly, the design of the literature search strategy, including the selection of search terms, required making decision choices on the part of the research team. Hence, we cannot formally guarantee that all papers on process mining in healthcare have been identified. However, the methodology was carefully designed to collect a broad range of relevant papers, e.g. by finetuning the search query using scoping searches. Moreover, the selection of papers was conducted in three databases, which were supplemented by two other databases to demonstrate that saturation was reached in terms of the collected literature. Secondly, as for any literature review, the information on which our analysis is based is limited to what has been explicitly reported in the paper. For review dimensions such as the process mining project stages and the involvement of domain experts, some efforts might have been done in reality, while they were not reflected in the paper. Reporting on such efforts is important as carefully considering the various stages of a process mining project and closely involving domain experts demonstrates the rigor of a process mining study. Moreover, increased transparency at the reporting level

also reduces the risk of a strong discrepancy between the actual execution of a process mining study and how it is reported in the paper.

6. Conclusion

This paper reported on the outcomes of an extensive systematic literature review on process mining in healthcare, covering 263 papers. Literature has been classified according to several dimensions, including three novel review dimensions that were not considered in prior reviews: (i) classifying the papers according to the process mining project stages, (i) the involvement of domain experts and (iii) the considered KPIs. Orthogonal to these three novel dimensions, we also highlight the evolution of the research domain by considering time trends within the review dimensions, which also distinguishes our review from prior work.

We can conclude that the results update, confirm, extend and enrich the insights from prior literature reviews on process mining in healthcare. The systematic classification of literature enabled us to discuss the current state of the field, as well as to share considerations regarding the future development of process mining in healthcare as a research domain. Our review clearly shows that process mining in healthcare is a research area in full development. Increasingly higher number of papers on a wide variety of topics have been published, signalling the presence of an active research community. A continuation of these efforts is needed, with specific attention for topics such as the translation of process mining outcomes to actionable ideas. In this way, process mining is likely to play an increasingly prominent role in instigating evidence-based process improvement in healthcare.

Appendix .	А.	Papers	classified	over	process	mining	project	stages
------------	----	--------	------------	------	---------	--------	---------	--------

Process mining project stages	Papers		
Project definition	[5, 6, 28, 29, 32, 33, 35, 37 - 39, 41 -		
	43,4547,49,5153,55,56,58		
	66, 68, 69, 72, 74, 76-83, 86, 89-92, 94-		
	$96, 98, 99, 101{-}104, 106, 108, 111{-}$		
	115,118165,165191]		
Data preparation	[5, 9, 27, 29, 30, 34 - 36, 38 -		
	42,44,45,47,5057,5962,64		
	$66,\ 68{-}90,\ 93{-}100,\ 100,\ 101,\ 103{-}$		
	105, 108, 110, 112, 113, 115, 118, 119,		
	122, 123, 125 - 139, 142, 144, 145, 149 -		
	151, 157-160, 162, 163, 165, 168, 169,		
	$171,173,175,178{-}182,184{-}$		
	186,189,190,192218]		
Process analysis	[5, 7, 9, 27 - 90, 92 - 116, 118 - 128, 130 -		
	$140,\ 142145,\ 147165,\ 167195,\ 197$		
	$206,\ 208{-}212,\ 214{-}224,\ 224{-}239]$		
Process redesign	[29, 46, 50, 51, 62, 64, 65, 82, 96, 111,		
	119, 127, 160, 238]		

Table A.1: Papers classified over process mining project stages

Appendix B. Papers classified under domain expert involvement steps

Involvement domain expert	Papers		
Problem identification	[9, 28–		
	30, 39, 42, 43, 47, 51, 59, 63, 76, 84, 90 -		
	94, 96-		
	103, 119, 139, 156, 159, 164, 178, 181		
Data extraction	[9, 27, 31, 39, 42, 63, 67, 70, 75, 76,		
	89, 90, 93, 94, 96, 98-		
	103, 115, 118, 119, 131, 139, 165, 170,		
	177, 178, 184, 187, 200, 214, 236]		
Data preparation	[27, 37, 39, 42, 51, 61, 63, 67, 76, 94-		
	103, 115, 119, 128, 135, 146, 165, 184,		
	194, 199, 204, 229]		
Interactive analysis	[9, 27, 31, 39, 42, 63, 67, 70, 75, 76,		
	89, 90, 93, 94, 96, 98-		
	103, 115, 118, 119, 131, 139, 165, 170,		
	177,178,184,187,200,214,236]		
Validation of gathered insights	[27, 29, 33, 36, 39, 41, 42, 46, 51, 52,		
	56,6365,68,76,79,86,89,94,96		
	103, 107, 115, 119, 130, 132, 133, 143,		
	147-149, 154-157, 162, 168, 173, 178,		
	179, 181, 185, 197, 198, 204, 205, 208,		
	210, 211, 215, 216, 229, 236, 240]		

Table B.2: Papers classified under domain expert involvement steps

KPI	Papers
Clinical	[30, 35, 52, 53, 61, 66, 67, 71, 72, 81,
	82, 94, 95, 98-
	100, 112, 113, 119, 121, 125, 126, 128,
	131, 134, 135, 137, 138, 146, 147, 149,
	155, 164, 173, 175, 184, 185, 187, 188,
	194,195,197,214,222,232,234,241-
	244]
Financial	[36, 39, 52, 66, 114, 115, 127, 190, 195]
Time	[5, 9, 29, 32, 39, 42, 43, 47, 52-56, 58-
	60, 62, 65, 74, 75, 82, 84, 85, 88, 89,
	94, 98–101, 103–
	111, 118, 119, 121, 123, 126, 127, 130,
	132, 137, 139, 145, 148–151, 154, 155,
	158, 160, 163, 167, 168, 177, 184, 185,
	189, 190, 193, 194, 197, 201, 203, 211,
	217, 219, 226, 233, 234, 239, 243, 245]
Resource	[52, 62, 84, 89, 101, 108, 118, 241]
No specific KPI considered	[3, 4, 7, 15, 16, 16-19, 21, 22, 27, 28,
	31, 33, 34, 37, 38, 40, 41, 44-46, 48-
	51, 57, 63, 64, 68 - 70, 73, 76 -
	80, 83, 86, 87, 90–93, 96, 102, 108,
	116, 120, 122, 124, 129, 133, 136, 140-
	144, 146, 152, 153, 157, 159, 161, 162,
	$165,166,169{-}174,176,178,180{-}$
	183,186,191,192,196,198-
	200, 202, 204–207, 209, 210, 212, 213,
	215, 216, 218, 220, 221, 223–225, 227–
	231, 235–238, 240, 246–278]

Appendix C. Papers classified according to the KPIs

Table C.3: Papers classified according to the KPIs

References

- R. Lenz, M. Reichert, It support for healthcare processes-premises, challenges, perspectives, Data & Knowledge Engineering 61 (1) (2007) 39–58.
- [2] W. van der Aalst, Process mining: data science in action, Springer, 2016.
- [3] A. Rule, M. F. Chiang, M. R. Hribar, Using electronic health record audit logs to study clinical activity: a systematic review of aims, measures, and methods, Journal of the American Medical Informatics Association 27 (3) (2020) 480–490.
- [4] N. Martin, J. De Weerdt, C. Fernández-Llatas, A. Gal, R. Gatta, G. Ibáñez, O. Johnson, F. Mannhardt, L. Marco-Ruiz, S. Mertens, et al., Recommendations for enhancing the usability and understandability of process mining in healthcare, Artificial Intelligence in Medicine 109 (2020) 101962.
- [5] O. Dogan, Process mining for check-up process analysis, IIOABJ 9 (6)
 (2018) 56–61.
- [6] H. Xu, J. Pang, X. Yang, L. Ma, H. Mao, D. Zhao, Applying clinical guidelines to conformance checking for diagnosis and treatment: a case study of ischemic stroke, in: 2020 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), IEEE, 2020, pp. 2125–2130.
- [7] O. Metsker, S. Kesarev, E. Bolgova, K. Golubev, A. Karsakov, A. Yakovlev, S. Kovalchuk, Modelling and analysis of complex patient-

treatment process using graphminer toolbox, in: International Conference on Computational Science, Springer, 2019, pp. 674–680.

- [8] C. Di Ciccio, A. Marrella, A. Russo, Knowledge-intensive processes: characteristics, requirements and analysis of contemporary approaches, Journal on Data Semantics 4 (1) (2015) 29–57.
- [9] A. Rebuge, D. R. Ferreira, Business process analysis in healthcare environments: A methodology based on process mining, Information systems 37 (2) (2012) 99–116.
- [10] L. Maruster, W. M. P. van der Aalst, A. J. M. M. Weijters, A. van den Bosch, W. Daelemans, Automated discovery of workflow models from hospital data, in: Proceedings of the 13th Belgium-Netherlands Conference on Artificial Intelligence, Citeseer, 2001, pp. 183–190.
- [11] M. R. Dallagassa, C. dos Santos Garcia, E. E. Scalabrin, S. O. Ioshii, D. R. Carvalho, Opportunities and challenges for applying process mining in healthcare: a systematic mapping study, Journal of Ambient Intelligence and Humanized Computing (2021) 1–18.
- [12] W. M. P. van der Aalst, A. J. M. M. Weijters, Process mining: a research agenda, Comput. Ind. 53 (3) (2004) 231–244.
- [13] L. Wen, W. M. P. van der Aalst, J. Wang, J. Sun, Mining process models with non-free-choice constructs, Data Mining and Knowledge Discovery 15 (2) (2007) 145–180.
- [14] M. Song, C. W. Günther, W. M. P. van der Aalst, Trace clustering in

process mining, Lecture Notes in Business Information Processing 17 (2009) 109–120.

- [15] E. Rojas, J. Munoz-Gama, M. Sepúlveda, D. Capurro, Process mining in healthcare: A literature review, Journal of biomedical informatics 61 (2016) 224–236.
- [16] M. Ghasemi, D. Amyot, Process mining in healthcare: a systematised literature review, International Journal of Electronic Healthcare 9 (1) (2016) 60–88.
- [17] E. Batista, A. Solanas, Process mining in healthcare: a systematic review, in: 2018 9th International Conference on Information, Intelligence, Systems and Applications (IISA), IEEE, 2018, pp. 1–6.
- [18] T. G. Erdogan, A. Tarhan, Systematic mapping of process mining studies in healthcare, IEEE Access 6 (2018) 24543–24567.
- [19] A. P. Kurniati, O. Johnson, D. Hogg, G. Hall, Process mining in oncology: A literature review, in: 2016 6th International Conference on Information Communication and Management (ICICM), IEEE, 2016, pp. 291–297.
- [20] G. P. Kusuma, M. Hall, C. P. Gale, O. A. Johnson, Process mining in cardiology: A literature review, International Journal of Bioscience, Biochemistry and Bioinformatics 8 (4) (2018) 226–236.
- [21] R. Williams, E. Rojas, N. Peek, O. A. Johnson, Process mining in primary care: A literature review, Studies in health technology and informatics 247 (2018) 376–380.

- [22] N. F. Farid, M. De Kamps, O. A. Johnson, Process mining in frail elderly care: a literature review, in: Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies-Volume 5: HEALTHINF, Vol. 5, SciTePress, Science and Technology Publications, 2019, pp. 332–339.
- [23] S. Aguirre, C. Parra, M. Sepúlveda, Methodological proposal for process mining projects, International Journal of Business Process Integration and Management 8 (2) (2017) 102–113.
- [24] N. Martin, B. Depaire, A. Caris, The use of process mining in business process simulation model construction, Business & Information Systems Engineering 58 (1) (2016) 73–87.
- [25] A. P. Hassler, E. Menasalvas, F. J. García-García, L. Rodríguez-Mañas, A. Holzinger, Importance of medical data preprocessing in predictive modeling and risk factor discovery for the frailty syndrome, BMC Medical Informatics and Decision Making 19 (1) (2019) 1–17.
- [26] P. M. Dixit, J. C. Buijs, W. M. van der Aalst, B. Hompes, J. Buurman, Using domain knowledge to enhance process mining results, in: International Symposium on Data-Driven Process Discovery and Analysis, Springer, 2015, pp. 76–104.
- [27] S. Mertens, F. Gailly, D. Van Sassenbroeck, G. Poels, Integrated declarative process and decision discovery of the emergency care process, Information Systems Frontiers (2020) 1–23.

- [28] S. Pereira Detro, E. A. P. Santos, H. Panetto, E. D. Loures, M. Lezoche, C. Cabral Moro Barra, Applying process mining and semantic reasoning for process model customisation in healthcare, Enterprise Information Systems 14 (7) (2020) 983–1009.
- [29] R. A. Q. Neira, B. F. A. Hompes, J. G.-J. de Vries, B. F. Mazza, S. L. S. de Almeida, E. Stretton, J. C. Buijs, S. Hamacher, Analysis and optimization of a sepsis clinical pathway using process mining, in: International Conference on Business Process Management, Springer, 2019, pp. 459–470.
- [30] M. A. Balakhontceva, A. A. Funkner, A. A. Semakova, O. G. Metsker, N. E. Zvartau, A. N. Yakovlev, A. E. Lutsenko, S. V. Kovalchuk, Holistic modeling of chronic diseases for recommendation elaboration and decision making, Procedia computer science 138 (2018) 228–237.
- [31] G. Riz, E. A. P. Santos, E. d. F. R. Loures, Process mining to knowledge discovery in healthcare processes, in: Transdisciplinary Engineering: Crossing Boundaries, IOS Press, 2016, pp. 1019–1028.
- [32] J. Poelmans, G. Dedene, G. Verheyden, H. Van der Mussele, S. Viaene,
 E. Peters, Combining business process and data discovery techniques for analyzing and improving integrated care pathways, in: Industrial Conference on Data Mining, Springer, 2010, pp. 505–517.
- [33] Z. Huang, W. Dong, L. Ji, L. Yin, H. Duan, On local anomaly detection and analysis for clinical pathways, Artificial intelligence in medicine 65 (3) (2015) 167–177.

- [34] K. Toth, K. Machalik, G. Fogarassy, A. Vathy-Fogarassy, Applicability of Process Mining in the Exploration of Healthcare Sequences, in: IEEE 30th Jubilee Neumann Colloquium, IEEE, 2017, pp. 151–155.
- [35] F. Marazza, F. A. Bukhsh, J. Geerdink, O. Vijlbrief, S. Pathak, M. v. Keulen, C. Seifert, Automatic process comparison for subpopulations: Application in cancer care, International journal of environmental research and public health 17 (16) (2020) 5707.
- [36] H. Huang, T. Jin, J. Wang, Extracting clinical-event-packages from billing data for clinical pathway mining, in: International Conference on Smart Health, Springer, 2016, pp. 19–31.
- [37] X. Xu, T. Jin, J. Wang, Summarizing patient daily activities for clinical pathway mining, in: IEEE 18th International Conference on e-Health Networking, Applications and Services, IEEE, 2016, pp. 194–199.
- [38] W.-S. Yang, S.-Y. Hwang, A process-mining framework for the detection of healthcare fraud and abuse, Expert Systems with Applications 31 (1) (2006) 56–68.
- [39] R. Gerhardt, J. F. Valiati, J. V. C. dos Santos, An investigation to identify factors that lead to delay in healthcare reimbursement process: a brazilian case, Big data research 13 (2018) 11–20.
- [40] M. R. Naeem, W. Ali, M. A. Hamad Naeem, W. A. Abro, A multi-level process mining framework for correlating and clustering of biomedical activities using event logs, International Journal of Advanced Computer Science and Applications 8 (3) (2017) 393–401.

- [41] C. Alvarez, E. Rojas, M. Arias, J. Munoz-Gama, M. Sepúlveda, V. Herskovic, D. Capurro, Discovering role interaction models in the emergency room using process mining, Journal of biomedical informatics 78 (2018) 60–77.
- [42] E. Rojas, A. Cifuentes, A. Burattin, J. Munoz-Gama, M. Sepúlveda, D. Capurro, Performance analysis of emergency room episodes through process mining, International journal of environmental research and public health 16 (7) (2019) 1274.
- [43] F. Mannhardt, D. Blinde, Analyzing the trajectories of patients with sepsis using process mining., in: RADAR+ EMISA@ CAiSE, 2017, pp. 72–80.
- [44] T. Mettiyaporn, K. Kungcharoen, W. Premchaiswadi, Using Transition Systems and Regions to Analyze and Monitor Admission Procedures of a Hospital, in: International Conference on ICT and Knowledge Engineering, International Conference on ICT and Knowledge Engineering, IEEE, 2016, pp. 105–108.
- [45] X. Xu, T. Jin, Z. Wei, C. Lv, J. Wang, TCPM: Topic-based Clinical Pathway Mining, in: Proceedings - 2016 IEEE 1st International Conference on Connected Health: Applications, Systems and Engineering Technologies, IEEE, 2016, pp. 292–301. doi:10.1109/CHASE.2016.17.
- [46] M. Rovani, F. M. Maggi, M. De Leoni, W. M. Van Der Aalst, Declarative process mining in healthcare, Expert Systems with Applications 42 (23) (2015) 9236–9251.

- [47] S. Suriadi, R. S. Mans, M. T. Wynn, A. Partington, J. Karnon, Measuring patient flow variations: A cross-organisational process mining approach, in: Asia-Pacific Conference on Business Process Management, Springer, 2014, pp. 43–58.
- [48] E. Kim, S. Kim, M. Song, S. Kim, D. Yoo, H. Hwang, S. Yoo, Discovery of outpatient care process of a tertiary university hospital using process mining, Healthcare informatics research 19 (1) (2013) 42–49.
- [49] T. Meneu, V. Traver, S. Guillén, B. Valdivieso, J. Benedí, C. Fernández-Llatas, Heart Cycle: Facilitating the deployment of advanced care processes, in: 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2013, pp. 6996– 6999.
- [50] N. Saelim, P. Porouhan, W. Premchaiswadi, Improving Organizational Process of a Hospital through Petri-Net Based Repair Models, in: International Conference on ICT and Knowledge Engineering, International Conference on ICT and Knowledge Engineering, IEEE, 2016, pp. 109–115.
- [51] K. F. Canjels, M. S. Imkamp, T. A. Boymans, R. J. Vanwersch, Unraveling and improving the interorganizational arthrosis care process at maastricht umc+: an illustration of an innovative, combined application of data and process mining., in: BPM (Industry Forum), 2019, pp. 178–189.
- [52] M. Cho, M. Song, J. Park, S.-R. Yeom, I.-J. Wang, B.-K. Choi,

Process mining-supported emergency room process performance indicators, International Journal of Environmental Research and Public Health 17 (17) (2020) 6290.

- [53] A. W. Kempa-Liehr, C. Y.-C. Lin, R. Britten, D. Armstrong, J. Wallace, D. Mordaunt, M. O'Sullivan, Healthcare pathway discovery and probabilistic machine learning, International journal of medical informatics 137 (2020) 104087.
- [54] S. Hirano, Temporal data mining on the stay time of outpatients and treatment processes, in: 2016 IEEE 16th International Conference on Data Mining Workshops (ICDMW), IEEE, 2016, pp. 527–530.
- [55] E. Lamine, F. Fontanili, M. Di Mascolo, H. Pingaud, Improving the management of an emergency call service by combining process mining and discrete event simulation approaches, in: Working Conference on Virtual Enterprises, Springer, 2015, pp. 535–546.
- [56] A. Partington, M. Wynn, S. Suriadi, C. Ouyang, J. Karnon, Process mining for clinical processes: a comparative analysis of four australian hospitals, ACM Transactions on Management Information Systems (TMIS) 5 (4) (2015) 1–18.
- [57] J. Lismont, A.-S. Janssens, I. Odnoletkova, S. vanden Broucke, F. Caron, J. Vanthienen, A guide for the application of analytics on healthcare processes: a dynamic view on patient pathways, Computers in biology and medicine 77 (2016) 125–134.

- [58] A. Pika, M. T. Wynn, S. Budiono, A. H. Ter Hofstede, W. M. van der Aalst, H. A. Reijers, Privacy-preserving process mining in healthcare, International journal of environmental research and public health 17 (5) (2020) 1612.
- [59] Z. Zhou, Y. Wang, L. Li, Process mining based modeling and analysis of workflows in clinical care-a case study in a chicago outpatient clinic, in: Proceedings of the 11th IEEE International Conference on Networking, Sensing and Control, IEEE, 2014, pp. 590–595.
- [60] S. N. Araghi, F. Fontanili, E. Lamine, N. Salatge, F. Benaben, Interpretation of patients' location data to support the application of process mining notations., in: HEALTHINF, 2020, pp. 472–481.
- [61] P. Weber, R. Backman, I. Litchfield, M. Lee, A process mining and text analysis approach to analyse the extent of polypharmacy in medical prescribing, in: 2018 IEEE International Conference on Healthcare Informatics (ICHI), IEEE, 2018, pp. 1–11.
- [62] A. Stefanini, D. Aloini, R. Dulmin, V. Mininno, Service reconfiguration in healthcare systems: the case of a new focused hospital unit, in: International Conference on Health Care Systems Engineering, Springer, 2017, pp. 179–188.
- [63] S. Montani, G. Leonardi, S. Quaglini, A. Cavallini, G. Micieli, Improving structural medical process comparison by exploiting domain knowledge and mined information, Artificial intelligence in medicine 62 (1) (2014) 33–45.

- [64] U. Kaymak, R. Mans, T. van de Steeg, M. Dierks, On Process Mining in Health Care, in: Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics, IEEE International Conference on Systems Man and Cybernetics Conference Proceedings, IEEE, 2012, pp. 1859–1864.
- [65] R. Mans, H. Reijers, M. van Genuchten, D. Wismeijer, Mining processes in dentistry, in: Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium, 2012, pp. 379–388.
- [66] R. Phan, V. Augusto, D. Martin, M. Sarazin, Clinical pathway analysis using process mining and discrete-event simulation: an application to incisional hernia, in: 2019 Winter Simulation Conference (WSC), IEEE, 2019, pp. 1172–1183.
- [67] S. Yang, F. Tao, J. Li, D. Wang, S. Chen, O. Z. Ahmed, I. Marsic, R. S. Burd, Process mining the trauma resuscitation patient cohorts, in: 2018 IEEE International Conference on Healthcare Informatics (ICHI), IEEE, 2018, pp. 29–35.
- [68] I. Litchfield, C. Hoye, D. Shukla, R. Backman, A. Turner, M. Lee, P. Weber, Can process mining automatically describe care pathways of patients with long-term conditions in uk primary care? a study protocol, BMJ open 8 (12) (2018) e019947.
- [69] A. Alharbi, A. Bulpitt, O. Johnson, Improving pattern detection in healthcare process mining using an interval-based event selection

method, in: International Conference on Business Process Management, Springer, 2017, pp. 88–105.

- [70] T. Toyawanit, W. Premchaiswadi, Applying inductive visual miner technique to analyze and detect problems in procedures of a hospital in thailand, in: 2016 14th International Conference on ICT and Knowledge Engineering (ICT&KE), IEEE, 2016, pp. 98–104.
- [71] E. S. Prokofyeva, R. D. Zaytsev, Clinical pathways analysis of patients in medical institutions based on hard and fuzzy clustering methods, -14 (1 (eng)) (2020).
- [72] A. Najjar, D. Reinharz, C. Girouard, C. Gagné, A two-step approach for mining patient treatment pathways in administrative healthcare databases, Artificial intelligence in medicine 87 (2018) 34–48.
- [73] P. de Toledo, C. Joppien, M. P. Sesmero, P. Drews, Mining disease courses across organizations: A methodology based on process mining of diagnosis events datasets, in: 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2019, pp. 354–357.
- [74] A. B. Durojaiye, S. Levin, M. Toerper, H. Kharrazi, H. P. Lehmann, A. P. Gurses, Evaluation of multidisciplinary collaboration in pediatric trauma care using ehr data, Journal of the American Medical Informatics Association 26 (6) (2019) 506–515.
- [75] M. Mesabbah, W. Abo-Hamad, S. McKeever, A hybrid process mining

framework for automated simulation modelling for healthcare, in: 2019 Winter Simulation Conference (WSC), IEEE, 2019, pp. 1094–1102.

- [76] S. Remy, L. Pufahl, J. P. Sachs, E. Böttinger, M. Weske, Event log generation in a health system: A case study, in: International Conference on Business Process Management, Springer, 2020, pp. 505–522.
- [77] A. P. Kurniati, E. Rojas, D. Hogg, G. Hall, O. A. Johnson, The assessment of data quality issues for process mining in healthcare using medical information mart for intensive care iii, a freely available e-health record database, Health informatics journal 25 (4) (2019) 1878–1893.
- [78] V. R. Vellore, M. A. Grando, B. Duncan, D. R. Kaufman, S. K. Furniss,
 B. N. Doebbeling, K. A. Poterack, T. Miksch, R. A. Helmers, Process Mining and Ethnography Study of Medication Reconciliation Tasks.
 2019 (2019) 1167–1176.
- [79] X. Lu, S. A. Tabatabaei, M. Hoogendoorn, H. A. Reijers, Trace Clustering on Very Large Event Data in Healthcare Using Frequent Sequence Patterns, in: Lecture Notes in Computer Science, Vol. 11675 of 17th International Conference on Business Process Management, BPM 2019, Springer Verlag, 2019, pp. 198–215.
- [80] G. Kukreja, S. Batra, Analogize Process Mining Techniques in Healthcare: Sepsis Case Study, in: M. Sood S, Jain (Eds.), 4th International Conference on Signal Processing, Computing and Control, IEEE International Conference on Signal Processing Computing and Control, IEEE, 2017, pp. 482–487.

- [81] F. Caron, J. Vanthienen, K. Vanhaecht, E. Van Limbergen, J. De Weerdt, B. Baesens, Monitoring care processes in the gynecologic oncology department, Computers in biology and medicine 44 (2014) 88–96.
- [82] R. Andrews, M. T. Wynn, K. Vallmuur, A. H. Ter Hofstede, E. Bosley, A comparative process mining analysis of road trauma patient pathways, International journal of environmental research and public health 17 (10) (2020) 3426.
- [83] D. A. R. Villamor, C. E. Pulmano, M. R. J. E. Estuar, Understanding adoption of electronic medical records: Application of process mining for health worker behavior analysis, in: Proceedings of the 4th International Conference on Medical and Health Informatics, 2020, pp. 98–104.
- [84] E. A. Elhadjamor, S. A. Ghannouchi, Analyze in depth health care business process and key performance indicators using process mining, Procedia Computer Science 164 (2019) 610–617.
- [85] K. Ganesha, M. Soundarya, K. Supriya V, The Best Fit Process Model for the Utilization of the Physical Resources in Hospitals by Applying Inductive Visual Miner, in: Proceedings of the International Conference on Inventive Communication and Computational Technologies, IEEE, 2017, pp. 318–322.
- [86] Z. Huang, C. Gan, X. Lu, H. Huan, Mining the changes of medical behaviors for clinical pathways, in: 14th World Congress on Medical

and Health Informatics, 14th World Congress on Medical and Health Informatics, MEDINFO 2013, IOS Press, 2013, pp. 117–121.

- [87] E. S. Prokofyeva, R. D. Zaytsev, S. V. Maltseva, Application of Modern Data Analysis Methods to Cluster the Clinical Pathways in Urban Medical Facilities, in: IEEE 21st Conference on Business Informatics, Vol. 1, 2019, pp. 75–83.
- [88] P. Jaisooki, W. Premchaiswadi, Time Performance Analysis of Medical Treatment Processes by using Disco, in: International Conference on ICT and Knowledge Engineering, International Conference on ICT and Knowledge Engineering, IEEE, 2015, pp. 110–115.
- [89] A. Stefanini, D. Aloini, E. Benevento, R. Dulmin, V. Mininno, Performance analysis in emergency departments: a data-driven approach, Measuring Business Excellence (2018).
- [90] D. M. Sato, S. C. de Freitas, M. R. Dallagassa, E. E. Scalabrin, E. A. Portela, D. R. Carvalho, Conformance checking with different levels of granularity: A case study on bariatric surgery, in: 2020 13th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), IEEE, 2020, pp. 820–826.
- [91] N. Abdullah, Y. Odeh, H. Saadeh, A. Iqniebi, A. Hassan, W. Nasser, M. Odeh, A. Tbakhi, Towards a process-based and service-oriented intelligent framework for ig/tcr clonality testing in suspected lymphoproliferative neoplasms, in: 2018 1st International Conference on Cancer Care Informatics (CCI), IEEE, 2018, pp. 165–179.

- [92] D. Duma, R. Aringhieri, Mining the patient flow through an emergency department to deal with overcrowding, in: International Conference on Health Care Systems Engineering, Springer, 2017, pp. 49–59.
- [93] S. K. Furniss, M. M. Burton, A. Grando, D. W. Larson, D. R. Kaufman, Integrating process mining and cognitive analysis to study ehr workflow, in: AMIA annual symposium proceedings, Vol. 2016, American Medical Informatics Association, 2016, p. 580.
- [94] A. B. Durojaiye, N. M. McGeorge, L. L. Puett, D. Stewart, J. C. Fackler, P. L. Hoonakker, H. P. Lehmann, A. P. Gurses, Mapping the flow of pediatric trauma patients using process mining, Applied clinical informatics 9 (03) (2018) 654–666.
- [95] H. De Oliveira, M. Prodel, L. Lamarsalle, M. Inada-Kim, K. Ajayi, J. Wilkins, S. Sekelj, S. Beecroft, S. Snow, R. Slater, et al., "bow-tie" optimal pathway discovery analysis of sepsis hospital admissions using the hospital episode statistics database in england, JAMIA open 3 (3) (2020) 439–448.
- [96] O. A. Johnson, T. B. Dhafari, A. Kurniati, F. Fox, E. Rojas, The clearpath method for care pathway process mining and simulation, in: International Conference on Business Process Management, Springer, 2018, pp. 239–250.
- [97] E. Benevento, P. M. Dixit, M. F. Sani, D. Aloini, W. M. van der Aalst, Evaluating the effectiveness of interactive process discovery in

healthcare: a case study, in: International Conference on Business Process Management, Springer, 2019, pp. 508–519.

- [98] G. P. Kusuma, S. Sykes, C. McInerney, O. Johnson, Process mining of disease trajectories: A feasibility study, in: HEALTHINF 2020 - 13th International Conference on Health Informatics, Proceedings; Part of 13th International Joint Conference on Biomedical Engineering Systems and Technologies, BIOSTEC 2020, 2020, pp. 705–712.
- [99] G. B. Pereira, E. A. P. Santos, M. M. C. Maceno, Process mining project methodology in healthcare: a case study in a tertiary hospital, Network Modeling Analysis in Health Informatics and Bioinformatics 9 (1) (2020) 1–14.
- [100] H. Xu, J. Pang, X. Yang, J. Yu, D. Zhao, A modeling approach based on multi-perspective declarative process mining for clinical activity, in: 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), IEEE, 2019, pp. 1688–1691.
- [101] J. A. Aguirre, A. C. Torres, M. E. Pescoran, Evaluation of operational process variables in healthcare using process mining and data visualization techniques, Health 7 (2019) 19.
- [102] S. Montani, G. Leonardi, S. Quaglini, A. Cavallini, G. Micieli, Knowledge-intensive medical process similarity, in: Workshop on Knowledge Representation for Health-Care Data, Processes and Guidelines, Springer, 2014, pp. 1–13.

- [103] A. P. Kurniati, C. McInerney, K. Zucker, G. Hall, D. Hogg, O. Johnson, Using a multi-level process comparison for process change analysis in cancer pathways, International Journal of Environmental Research and Public Health 17 (19) (2020) 7210.
- [104] H. Baek, M. Cho, S. Kim, H. Hwang, M. Song, S. Yoo, Analysis of length of hospital stay using electronic health records: A statistical and data mining approach, PloS one 13 (4) (2018) e0195901.
- [105] S. V. Kovalchuk, A. A. Funkner, O. G. Metsker, A. N. Yakovlev, Simulation of patient flow in multiple healthcare units using process and data mining techniques for model identification, Journal of biomedical informatics 82 (2018) 128–142.
- [106] K. Helbig, M. Römer, T. Mellouli, A clinical pathway mining approach to enable scheduling of hospital relocations and treatment services, in: International Conference on Business Process Management, Springer, 2016, pp. 242–250.
- [107] Z. Huang, Z. Ge, W. Dong, K. He, H. Duan, Probabilistic modeling personalized treatment pathways using electronic health records, Journal of biomedical informatics 86 (2018) 33–48.
- [108] E. Benevento, D. Aloini, N. Squicciarini, R. Dulmin, V. Mininno, Queue-based features for dynamic waiting time prediction in emergency department, Measuring Business Excellence 23 (4) (2019) 458–471.
- [109] K. Ganesha, S. Dhanush, S. S. M. Raj, An Approach to Fuzzy Process Mining to Reduce Patient Waiting Time in a Hospital, in: Proceed-

ings of 2017 International Conference on Innovations in Information, Embedded and Communication Systems, IEEE, 2017.

- [110] H. J. Yeo, Medical service improvement through patient's queue decision mining, Journal of Theoretical & Applied Information Technology 95 (18) (2017) 4853–4861.
- [111] B. B. Antunes, A. Manresa, L. S. Bastos, J. F. Marchesi, S. Hamacher, A solution framework based on process mining, optimization, and discrete-event simulation to improve queue performance in an emergency department, in: International Conference on Business Process Management, Springer, 2019, pp. 583–594.
- [112] G. J. De Vries, R. A. Q. Neira, G. Geleijnse, P. Dixit, B. F. Mazza, Towards process mining of EMR data case study for sepsis management, in: HEALTHINF 2017 - 10th International Conference on Health Informatics, Proceedings; Part of 10th International Joint Conference on Biomedical Engineering Systems and Technologies, Vol. 5, 2017, pp. 585–593.
- [113] F. Lu, P. Li, Y. Bao, C. Liu, Q. Zeng, Death risk prediction of intensive care unit patients combined with treatment process mining, Journal of Medical Imaging and Health Informatics 10 (7) (2020) 1754–1762.
- [114] S. Van Der Spoel, M. Van Keulen, C. Amrit, Process prediction in noisy data sets: a case study in a dutch hospital, in: International Symposium on Data-Driven Process Discovery and Analysis, Springer, 2012, pp. 60–83.

- [115] S. Dahlin, H. Raharjo, Relationship between patient costs and patient pathways., International journal of health care quality assurance 32 (1) (2019) 246–261.
- [116] S. Montani, M. Striani, S. Quaglini, A. Cavallini, G. Leonardi, Knowledge-based trace abstraction for semantic process mining, in: Conference on Artificial Intelligence in Medicine in Europe, Springer, 2017, pp. 267–271.
- [117] C. dos Santos Garcia, A. Meincheim, E. R. F. Junior, M. R. Dallagassa, D. M. V. Sato, D. R. Carvalho, E. A. P. Santos, E. E. Scalabrin, Process mining techniques and applications-a systematic mapping study, Expert Systems with Applications 133 (2019) 260–295.
- [118] W. Abo-Hamad, Patient pathways discovery and analysis using process mining techniques: An emergency department case study, in: International Conference on Health Care Systems Engineering, Springer, 2017, pp. 209–219.
- [119] S. Agostinelli, F. Covino, G. D'Agnese, C. De Crea, F. Leotta, A. Marrella, Supporting governance in healthcare through process mining: A case study, IEEE Access 8 (2020) 186012–186025.
- [120] A. Alharbi, A. Bulpitt, O. A. Johnson, Towards unsupervised detection of process models in healthcare., in: MIE, 2018, pp. 381–385.
- [121] I. A. Amantea, E. Sulis, G. Boella, R. Marinello, D. Bianca,E. Brunetti, M. Bo, C. Fernandez-Llatas, A process mining applica-

tion for the analysis of hospital-at-home admissions., Studies in health technology and informatics 270 (2020) 522–526.

- [122] R. Andrews, M. T. Wynn, K. Vallmuur, A. H. ter Hofstede, E. Bosley, M. Elcock, S. Rashford, Pre-hospital retrieval and transport of road trauma patients in queensland, in: International Conference on Business Process Management, Springer, 2018, pp. 199–213.
- [123] R. Anggrainingsih, B. O. P. Johannanda, D. E. Cahyani, Business process evaluation of outpatient services using process mining, Journal of Telecommunication, Electronic and Computer Engineering (JTEC) 10 (2-4) (2018) 125–128.
- [124] S. N. Araghi, F. Fontaili, E. Lamine, N. Salatge, J. Lesbegueries, S. R. Pouyade, L. Tancerel, F. Benaben, A conceptual framework to support discovering of patients' pathways as operational process charts, in: 2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA), IEEE, 2018, pp. 1–6.
- [125] E. Asare, L. Wang, X. Fang, Conformance checking: Workflow of hospitals and workflow of open-source emrs, IEEE Access 8 (2020) 139546– 139566.
- [126] C. Olling Back, A. Manataki, E. Harrison, Mining patient flow patterns in a surgical ward, in: Proceedings of the 13th International Joint Conference on Biomedical Engineering Systems and Technologies, SciTePress, 2020.
- [127] P. Badakhshan, A. Alibabaei, Using process mining for process analysis improvement in pre-hospital emergency, in: ICT for an Inclusive World, Springer, 2020, pp. 567–580.
- [128] G. Battineni, N. Chintalapudi, F. Amenta, Model discovery, and replay fitness validation using inductive mining techniques in medical training of cvc surgery, Applied Computing and Informatics (2020).
- [129] L. Bouarfa, J. Dankelman, Workflow mining and outlier detection from clinical activity logs, Journal of Biomedical Informatics 45 (6) (2012) 1185–1190.
- [130] H. Chang, J. Y. Yu, S. Y. Yoon, S. Y. Hwang, H. Yoon, W. C. Cha, M. S. Sim, I. J. Jo, T. Kim, Impact of covid-19 pandemic on the overall diagnostic and therapeutic process for patients of emergency department and those with acute cerebrovascular disease, Journal of clinical medicine 9 (12) (2020) 3842.
- [131] M. Cho, K. Kim, J. Lim, H. Baek, S. Kim, H. Hwang, M. Song, S. Yoo, Developing data-driven clinical pathways using electronic health records: The cases of total laparoscopic hysterectomy and rotator cuff tears, International Journal of Medical Informatics 133 (2020) 104015.
- [132] M. Cho, M. Song, S. Yoo, H. A. Reijers, An evidence-based decision support framework for clinician medical scheduling, IEEE Access 7 (2019) 15239–15249.

- [133] T. Conca, C. Saint-Pierre, V. Herskovic, M. Sepúlveda, D. Capurro, F. Prieto, C. Fernandez-Llatas, Multidisciplinary collaboration in the treatment of patients with type 2 diabetes in primary care: analysis using process mining, Journal of Medical Internet Research 20 (4) (2018) e8884.
- [134] A. Dagliati, L. Sacchi, C. Cerra, P. Leporati, P. De Cata, L. Chiovato, J. H. Holmes, R. Bellazzi, Temporal Data Mining and Process Mining Techniques to Identify Cardiovascular Risk-Associated Clinical Pathways in Type 2 Diabetes Patients, in: IEEE-EMBS International Conference on Biomedical and Health Informatics, IEEE, 2014, pp. 240–243.
- [135] R. de la Fuente, R. Fuentes, J. Munoz-Gama, A. Riquelme, F. R. Altermatt, J. Pedemonte, M. Corvetto, M. Sepúlveda, Control-flow analysis of procedural skills competencies in medical training through process mining, Postgraduate medical journal 96 (1135) (2020) 250–256.
- [136] J. De Weerdt, F. Caron, J. Vanthienen, B. Baesens, Getting a grasp on clinical pathway data: an approach based on process mining, in: Pacific-Asia Conference on Knowledge Discovery and Data Mining, Springer, 2012, pp. 22–35.
- [137] D. Duma, R. Aringhieri, An ad hoc process mining approach to discover patient paths of an emergency department, Flexible Services and Manufacturing Journal 32 (1) (2020) 6–34.
- [138] E. S. Prokofyeva, S. V. Maltseva, N. Y. Fomichev, A. G. Kudryashov,

Data-Driven Approach To Patient Flow Management And Resource Utilization In Urban Medical Facilities, in: IEEE 22nd Conference on Business Informatics, Vol. 2, 2020, pp. 71–77.

- [139] T. Gurgen Erdogan, A. Tarhan, A goal-driven evaluation method based on process mining for healthcare processes, Applied Sciences 8 (6) (2018) 894.
- [140] C. Fernández-Llatas, J.-M. Benedi, J. M. García-Gómez, V. Traver, Process mining for individualized behavior modeling using wireless tracking in nursing homes, Sensors 13 (11) (2013) 15434–15451.
- [141] C. Fernandez-Llatas, T. Meneu, J. M. Benedi, V. Traver, Activitybased process mining for clinical pathways computer aided design., in: 2010 Annual International Conference of the IEEE Engineering in Medicine and Biology, 2010, pp. 6178–6181.
- [142] C. Fernandez-Llatas, L. Sacchi, J. M. Benedi, A. Dagliati, V. Traver, R. Bellazzi, Temporal Abstractions to enrich Activity-Based Process Mining Corpus with clinical time series., in: IEEE-EMBS International Conference on Biomedical and Health Informatics, IEEE, 2014, pp. 785–788.
- [143] C. Fernandez-Llatas, A. Lizondo, E. Monton, J.-M. Benedi, V. Traver, Process mining methodology for health process tracking using real-time indoor location systems, Sensors 15 (12) (2015) 29821–29840.
- [144] D. Forsberg, B. Rosipko, J. L. Sunshine, Analyzing pacs usage patterns

by means of process mining: steps toward a more detailed workflow analysis in radiology, Journal of digital imaging 29 (1) (2016) 47–58.

- [145] A. A. Funkner, A. N. Yakovlev, S. V. Kovalchuk, Data-driven modeling of clinical pathways using electronic health records, Vol. 121, Elsevier, 2017, pp. 835–842.
- [146] A. A. Funkner, A. N. Yakovlev, S. V. Kovalchuk, Towards evolutionary discovery of typical clinical pathways in electronic health records, Vol. 119, Elsevier, 2017, pp. 234–244.
- [147] V. Galvez, R. de la Fuente, C. Meneses, L. Leiva, G. Fagalde, V. Herskovic, R. Fuentes, J. Munoz-Gama, M. Sepúlveda, Process-oriented instrument and taxonomy for teaching surgical procedures in medical training: The ultrasound-guided insertion of central venous catheter, International Journal of Environmental Research and Public Health 17 (11) (2020) 3849.
- [148] E. Gattnar, O. Ekinci, V. Detschew, A novel way of standardized and automized retrieval of timing information along clinical pathways, in: User Centred Networked Health Care, IOS Press, 2011, pp. 507–511.
- [149] J. González-García, C. Tellería-Orriols, F. Estupiñán-Romero, E. Bernal-Delgado, Construction of empirical care pathways process models from multiple real-world datasets, IEEE Journal of Biomedical and Health Informatics 24 (9) (2020) 2671–2680.
- [150] A. Grando, D. Groat, S. K. Furniss, J. Nowak, R. Gaines, D. R. Kaufman, K. A. Poterack, T. Miksch, R. A. Helmers, Using process mining

techniques to study workflows in a pre-operative setting, in: AMIA annual symposium proceedings, Vol. 2017, American Medical Informatics Association, 2017, p. 790.

- [151] A. Grando, A. Manataki, S. K. Furniss, B. Duncan, A. Solomon, D. Kaufman, S. Hirn, R. Sunday, J. Bouchereau, B. Doebbeling, et al., Multi-method study of electronic health records workflows, in: AMIA annual symposium proceedings, Vol. 2018, American Medical Informatics Association, 2018, p. 498.
- [152] R. M. Hendricks, Process mining of incoming patients with sepsis, Online journal of public health informatics 11 (2) (2019).
- [153] Z. Huang, Y. Bao, W. Dong, X. Lu, H. Duan, Online treatment compliance checking for clinical pathways, Journal of medical systems 38 (10) (2014) 1–14.
- [154] Z. Huang, W. Dong, L. Ji, C. Gan, X. Lu, H. Duan, Discovery of clinical pathway patterns from event logs using probabilistic topic models, Journal of biomedical informatics 47 (2014) 39–57.
- [155] Z. Huang, X. Lu, H. Duan, On mining clinical pathway patterns from medical behaviors, Artificial intelligence in medicine 56 (1) (2012) 35– 50.
- [156] Z. Huang, W. Dong, P. Bath, L. Ji, H. Duan, On mining latent treatment patterns from electronic medical records, Data mining and knowledge discovery 29 (4) (2015) 914–949.

- [157] Z. Huang, X. Lu, H. Duan, W. Fan, Summarizing clinical pathways from event logs, Journal of Biomedical Informatics 46 (1) (2013) 111– 127.
- [158] G. Ibanez-Sanchez, C. Fernandez-Llatas, A. Martinez-Millana, A. Celda, J. Mandingorra, L. Aparici-Tortajada, Z. Valero-Ramon, J. Munoz-Gama, M. Sepúlveda, E. Rojas, et al., Toward value-based healthcare through interactive process mining in emergency rooms: the stroke case, International journal of environmental research and public health 16 (10) (2019) 1783.
- [159] J. Pebesma, A. Martinez-Millana, L. Sacchi, C. Fernandez-Llatas, P. D. Cata, L. Chiovato, R. Bellazzi, V. Traver, Clustering Cardiovascular Risk Trajectories of Patients with Type 2 Diabetes Using Process Mining, in: 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2019, pp. 341–344.
- [160] K. Rajakumari, M. Madhunisha, Intelligent and Convolutional-Neural-Network based Smart Hospital and Patient Scheduling System, in: International Conference on Computer Communication and Informatics, 2020, pp. 1–5.
- [161] K. Kirchner, P. Marković, Unveiling hidden patterns in flexible medical treatment processes-a process mining case study, in: International Conference on Decision Support System Technology, Springer, 2018, pp. 169–180.
- [162] J. Koorn, X. Lu, H. Leopold, H. A. Reijers, Towards understanding

aggressive behavior in residential care facilities using process mining, in: International Conference on Conceptual Modeling, Springer, 2019, pp. 135–145.

- [163] A. P. Kurniati, G. Hall, D. Hogg, O. Johnson, Process mining in oncology using the mimic-iii dataset, in: Journal of Physics: Conference Series, Vol. 971, IOP Publishing, 2018, p. 012008.
- [164] G. Leonardi, M. Striani, S. Quaglini, A. Cavallini, S. Montani, Leveraging semantic labels for multi-level abstraction in medical process mining and trace comparison, Journal of Biomedical Informatics 83 (2018) 10–24.
- [165] R. Lira, J. Salas-Morales, L. Leiva, R. Fuentes, A. Delfino, C. H. Nazal, M. Sepúlveda, M. Arias, V. Herskovic, J. Munoz-Gama, et al., Processoriented feedback through process mining for surgical procedures in medical training: The ultrasound-guided central venous catheter placement case, International journal of environmental research and public health 16 (11) (2019) 1877.
- [166] M. Zhou, S. Yang, X. Li, S. Lv, S. Chen, I. Marsic, R. A. Farneth, R. S. Burd, Evaluation of trace alignment quality and its application in medical process mining, in: 2017 IEEE International Conference on Healthcare Informatics (ICHI), IEEE, 2017, pp. 258–267.
- [167] R. Mans, H. Schonenberg, G. Leonardi, S. Panzarasa, A. Cavallini, S. Quaglini, W. Van Der Aalst, Process mining techniques: an application to stroke care, in: MIE, Vol. 136, 2008, pp. 573–578.

- [168] R. S. Mans, M. H. Schonenberg, M. Song, W. M. P. van der Aalst, P. J. M. Bakker, Process mining in healthcare - A case study, in: Healthinf 2008: Proceedings of the First International Conference on Health Informatics, Scitepress, 2008, pp. 118–125.
- [169] F. Marazza, F. A. Bukhsh, O. Vijlbrief, J. Geerdink, S. Pathak, M. van Keulen, C. Seifert, Comparing process models for patient populations: application in breast cancer care, in: International Conference on Business Process Management, Springer, 2019, pp. 496–507.
- [170] A. Martinez-Millana, A. Lizondo, R. Gatta, S. Vera, V. T. Salcedo, C. Fernandez-Llatas, Process mining dashboard in operating rooms: Analysis of staff expectations with analytic hierarchy process, International journal of environmental research and public health 16 (2) (2019) 199.
- [171] N. Martin, A. Martinez-Millana, B. Valdivieso, C. Fernández-Llatas, Interactive data cleaning for process mining: a case study of an outpatient clinic's appointment system, in: International Conference on Business Process Management, Springer, 2019, pp. 532–544.
- [172] C. McGregor, C. Catley, A. James, A process mining driven framework for clinical guideline improvement in critical care, in: Proceedings of the Learning from Medical Data Streams Workshop, Vol. 765, 2011.
- [173] O. Metsker, E. Bolgova, A. Yakovlev, A. Funkner, S. Kovalchuk, Pattern-based mining in electronic health records for complex clinical process analysis, Procedia Computer Science 119 (2017) 197–206.

- [174] R. Miclo, F. Fontanili, G. Marques, P. Bornert, M. Lauras, RTLS-based Process Mining: Towards an Automatic Process Diagnosis in Healthcare, in: IEEE International Conference on Automation Science and Engineering, IEEE International Conference on Automation Science and Engineering, IEEE, 2015, pp. 1397–1402.
- [175] M. Miranda, S. Salvatierra, I. Rodríguez, M. Alvarez, V. Rodríguez, Characterization of the flow of patients in a hospital from complex networks, Health care management science 23 (1) (2020) 66–79.
- [176] S. Montani, G. Leonardi, S. Quaglini, A. Cavallini, G. Micieli, Mining and retrieving medical processes to assess the quality of care, in: Lecture Notes in Computer Science, Vol. 7969 of 21st International Conference on Case-Based Reasoning Research and Development, IC-CBR 2013, 2013, pp. 233–240.
- [177] S. Oueida, Y. Kotb, Healthcare emergency room optimization using a process learning algorithm, in: Proceedings of the Future Technologies Conference, Springer, 2020, pp. 46–63.
- [178] L. Perimal-Lewis, D. De Vries, C. H. Thompson, Health intelligence: Discovering the process model using process mining by constructing start-to-end patient journeys, in: Proceedings of the Seventh Australasian Workshop on Health Informatics and Knowledge Management-Volume 153, 2014, pp. 59–67.
- [179] C. Rinner, E. Helm, R. Dunkl, H. Kittler, S. Rinderle-Ma, Process mining and conformance checking of long running processes in the con-

text of melanoma surveillance, International journal of environmental research and public health 15 (12) (2018) 2809.

- [180] C. Rinner, E. Helm, R. Dunkl, H. Kittler, S. Rinderle-Ma, An application of process mining in the context of melanoma surveillance using time boxing, in: International Conference on Business Process Management, Springer, 2018, pp. 175–186.
- [181] E. Rojas, M. Sepúlveda, J. Munoz-Gama, D. Capurro, V. Traver, C. Fernandez-Llatas, Question-driven methodology for analyzing emergency room processes using process mining, Applied Sciences 7 (3) (2017) 302.
- [182] E. Rojas, D. Capurro, Characterization of drug use patterns using process mining and temporal abstraction digital phenotyping, in: International Conference on Business Process Management, Springer, 2018, pp. 187–198.
- [183] M. Ruffolo, R. Curia, L. Gallucci, Process management in health care: A system for preventing risks and medical errors, in: International Conference on Business Process Management, Springer, 2005, pp. 334– 343.
- [184] D. M. Sato, L. K. Mantovani, J. Safanelli, V. Guesser, V. Nagel, C. H. Moro, N. L. Cabral, E. E. Scalabrin, C. Moro, E. A. Santos, Ischemic stroke: Process perspective, clinical and profile characteristics, and external factors, Journal of Biomedical Informatics 111 (2020) 103582.

- [185] A. Stefanini, D. Aloini, E. Benevento, R. Dulmin, V. Mininno, A datadriven methodology for supporting resource planning of health services, Socio-Economic Planning Sciences 70 (2020) 100744.
- [186] A. Stefanini, D. Aloini, R. Dulmin, V. Mininno, Linking diagnosticrelated groups (drgs) to their processes by process mining., HEALTH-INF 5 (2016) 438–443.
- [187] R. Williams, D. M. Ashcroft, B. Brown, E. Rojas, N. Peek, O. A. Johnson, Process mining in primary care: Avoiding adverse events due to hazardous prescribing., in: MedInfo, 2019, pp. 447–451.
- [188] C. Yan, Y. Chen, B. Li, D. Liebovitz, B. Malin, Learning Clinical Workflows to Identify Subgroups of Heart Failure Patients, in: AMIA Annual Symposium Proceedings, Vol. 2016, 2016, pp. 1248–1257.
- [189] S. Yoo, M. Cho, E. Kim, S. Kim, Y. Sim, D. Yoo, H. Hwang, M. Song, Assessment of hospital processes using a process mining technique: Outpatient process analysis at a tertiary hospital., International journal of medical informatics 88 (2016) 34–43.
- [190] Z. Chai, L. Ding, S. Xu, The hospital outpatient process mining algorithm based on improved chaos genetic algorithm, in: 2020 Chinese Control And Decision Conference (CCDC), IEEE, 2020, pp. 4495–4540.
- [191] X. Zhang, S. Chen, Pathway Identification via Process Mining for Patients with Multiple Conditions, in: IEEE International Conference on Industrial Engineering and Engineering Management, International

Conference on Industrial Engineering and Engineering Management IEEM, IEEE, 2012, pp. 1754–1758.

- [192] D. Antonelli, G. Bruno, Application of process mining and semantic structuring towards a lean healthcare network, in: Working Conference on Virtual Enterprises, Springer, 2015, pp. 497–508.
- [193] S. N. Araghi, F. Fontanili, E. Lamine, L. Tancerel, F. Benaben, Monitoring and analyzing patients' pathways by the application of Process Mining, SPC, and I-RTLS, IFAC-PapersOnLine 51 (11) (2018) 980– 985.
- [194] M. Arias, E. Rojas, S. Aguirre, F. Cornejo, J. Munoz-Gama, M. Sepúlveda, D. Capurro, Mapping the Patient's Journey in Healthcare through Process Mining., International Journal of Environmental Research and Public Health 17 (18) (2020) 1–16.
- [195] V. Augusto, X. Xie, M. Prodel, B. Jouaneton, L. Lamarsalle, Evaluation of discovered clinical pathways using process mining and joint agent-based discrete-event simulation, in: Proceedings - Winter Simulation Conference, Winter Simulation Conference Proceedings, IEEE, 2016, pp. 2135–2146.
- [196] K. Bakera, E. Dunwoodie, R. G. Jones, A. Newsham, O. Johnson, C. P. Price, J. Wolstenholme, J. Leal, P. McGinley, C. Twelves, G. Hall, Process mining routinely collected electronic health records to define real-life clinical pathways during chemotherapy, International journal of medical informatics 103 (2017) 32–41.

- [197] L. Chiudinelli, A. Dagliati, V. Tibollo, S. Albasini, N. Geifman, N. Peek, J. H. Holmes, F. Corsi, R. Bellazzi, L. Sacchi, Mining postsurgical care processes in breast cancer patients., Artificial Intelligence in Medicine 105 (2020) 101855.
- [198] M. Cho, M. Song, S. Yoo, A systematic methodology for outpatient process analysis based on process mining, in: Asia-Pacific Conference on Business Process Management, Springer, 2014, pp. 31–42.
- [199] A. Dagliati, V. Tibollo, G. Cogni, L. Chiovato, R. Bellazzi, L. Sacchi, Careflow mining techniques to explore type 2 diabetes evolution, Journal of diabetes science and technology 12 (2) (2018) 251–259.
- [200] T. Doleck, A. Jarrell, E. G. Poitras, M. Chaouachi, S. P. Lajoie, Examining Diagnosis Paths: A Process Mining Approach, in: Second International Conference on Computational Intelligence Communication Technology, IEEE, 2016, pp. 663–667.
- [201] K. Ganesha, K. Supriya, M. Soundarya, Analyzing the waiting time of patients in hospital by applying heuristics process miner, in: 2017 International Conference on Inventive Communication and Computational Technologies (ICICCT), IEEE, 2017, pp. 500–505.
- [202] K. Jangvaha, P. Porouhan, P. Palangsantikul, W. Premchaiswadi, Analysis of Emergency Room Service using Fuzzy Process Mining Technique, in: International Conference on ICT and Knowledge Engineering, International Conference on ICT and Knowledge Engineering, IEEE, 2017, pp. 118–122.

- [203] T. Jaturogpattana, P. Arpasat, K. Kungcharoen, S. Intarasema, W. Premchaiswadi, Conformance Analysis of Outpatient Data Using Process Mining Technique, in: International Conference on ICT and Knowledge Engineering, International Conference on ICT and Knowledge Engineering, IEEE, 2017, pp. 102–107.
- [204] G. T. Lakshmanan, S. Rozsnyai, F. Wang, Investigating clinical care pathways correlated with outcomes, in: Lecture Notes in Computer Science, Vol. 8094 of 11th International Conference on Business Process Management, BPM 2013, 2013, pp. 323–338.
- [205] R. S. Mans, M. Schonenberg, M. Song, W. M. van der Aalst, P. J. Bakker, Application of process mining in healthcare–a case study in a dutch hospital, in: International joint conference on biomedical engineering systems and technologies, Springer, 2008, pp. 425–438.
- [206] N. Martin, L. Pufahl, F. Mannhardt, Detection of batch activities from event logs, Information Systems 95 (2021) 101642.
- [207] N. Martin, Using indoor location system data to enhance the quality of healthcare event logs: opportunities and challenges, in: International Conference on Business Process Management, Springer, 2018, pp. 226– 238.
- [208] O. Metsker, A. Yakovlev, E. Bolgova, A. Vasin, S. Koval-chuk, Identification of pathophysiological subclinical variances during complex treatment process of cardiovascular patients, Procedia computer science 138 (2018) 161–168.

- [209] W. Neamsirorat, W. Premchaiswadi, Analysis of Surgical Event Logs in a Hospital by using Heuristics Miner Technique, in: International Conference on ICT and Knowledge Engineering, International Conference on ICT and Knowledge Engineering, IEEE, 2015, pp. 105–109.
- [210] M. Prodel, V. Augusto, X. Xie, B. Jouaneton, L. Lamarsalle, Discovery of patient pathways from a national hospital database using Process Mining and Integer Linear Programming, in: IEEE International Conference on Automation Science and Engineering, IEEE International Conference on Automation Science and Engineering, IEEE, 2015, pp. 1409–1414.
- [211] Á. Rebuge, L. V. Lapão, A. Freitas, R. Cruz-Correia, A process mining analysis on a virtual electronic patient record system, in: Proceedings of the 26th IEEE International Symposium on Computer-Based Medical Systems, IEEE, 2013, pp. 554–555.
- [212] F. Rismanchian, Y. H. Lee, Process Mining–Based Method of Designing and Optimizing the Layouts of Emergency Departments in Hospitals, HERD: Health Environments Research & Design Journal 10 (4) (2017) 105–120.
- [213] H. Syed, A. K. Das, Temporal needleman-wunsch, in: 2015 IEEE International Conference on Data Science and Advanced Analytics (DSAA), IEEE, 2015, pp. 1–9.
- [214] Z. Valero-Ramon, A. Martinez-Millana, V. Traver, C. Fernandez-Llatas, Dynamic risk models supporting personalised diabetes health-

care with process mining, in: Diabetes Technology & Therapeutics, Vol. 22, 2020, p. A112.

- [215] H. Xu, J. Pang, X. Yang, J. Yu, H. Mao, D. Zhao, A case study of conformance checking for diagnosis and treatment of ischemic stroke based on clinical guidelines, in: C. F., F. A., G. H. (Eds.), International Conference on Health Informatics, SciTePress, 2020, pp. 571–578.
- [216] H. Xu, J. Pang, X. Yang, M. Li, D. Zhao, Using predictive process monitoring to assist thrombolytic therapy decision-making for ischemic stroke patients, BMC Medical Informatics and Decision Making 20 (3) (2020) 1–10.
- [217] T. Yampaka, P. Chongstitvatana, An Application of Process Mining for Queueing System in Health Service, in: 13th International Joint Conference on Computer Science and Software Engineering, International Joint Conference on Computer Science and Software Engineering, IEEE, 2016, pp. 161–166.
- [218] Y. Zhang, R. Padman, N. Patel, Paving the cowpath: Learning and visualizing clinical pathways from electronic health record data, Journal of biomedical informatics 58 (2015) 186–197.
- [219] S. N. Araghi, F. Fontanili, E. Lamine, N. Salatge, J. Lesbegueries, S. R. Pouyade, F. Benaben, Evaluating the process capability ratio of patients' pathways by the application of process mining, spc and rtls., in: HEALTHINF, 2019, pp. 302–309.

- [220] I. V. Arnolds, D. Gartner, Improving hospital layout planning through clinical pathway mining, Annals of operations research 263 (1) (2018) 453–477.
- [221] W. Chomyat, W. Premchaiswadi, Process Mining on Medical Treatment History Using Conformance Checking, in: 14th International Conference on ICT and Knowledge Engineering, International Conference on ICT and Knowledge Engineering, IEEE, 2016, pp. 77–83.
- [222] H. De Oliveira, V. Augusto, B. Jouaneton, L. Lamarsalle, M. Prodel, X. Xie, Automatic and explainable labeling of medical event logs with autoencoding, IEEE Journal of Biomedical and Health Informatics 24 (11) (2020) 3076–3084.
- [223] S. P. Detro, E. A. P. Santos, H. Panetto, E. d. F. R. Loures, M. Lezoche, Managing business process variability through process mining and semantic reasoning: An application in healthcare, in: Working Conference on Virtual Enterprises, Springer, 2017, pp. 333–340.
- [224] C. Fernandez-Llatas, J. L. Bayo, A. Martinez-Romero, J. M. Benedi, V. Traver, Interactive Pattern Recognition in Cardiovascular Disease Management. A Process Mining approach, in: IEEE-EMBS International Conference on Biomedical and Health Informatics, IEEE, 2016, pp. 348–351.
- [225] C. Fernandez-Llatas, A. Martinez-Millana, A. Martinez-Romero, J. M. Benedi, V. Traver, Diabetes care related process modelling using process mining techniques. lessons learned in the application of interactive

pattern recognition: coping with the spaghetti effect, in: 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC), IEEE, 2015, pp. 2127–2130.

- [226] K. Ganesha, S. S. M. Raj, S. Dhanush, Process mining approach for efficient utilization of resources in a hospital, in: Proceedings of 2017 International Conference on Innovations in Information, Embedded and Communication Systems, IEEE, 2017.
- [227] N. Garg, S. Agarwal, Process mining for clinical workflows, in: Proceedings of the International Conference on Advances in Information Communication Technology & Computing, 2016, pp. 1–5.
- [228] M. A. Grando, M. Schonenberg, W. M. van der Aalst, Semantic process mining for the verification of medical recommendations., in: HEALTH-INF, 2011, pp. 5–16.
- [229] Z. Huang, X. Lu, H. Duan, Latent treatment pattern discovery for clinical processes, Journal of medical systems 37 (2) (2013) 1–10.
- [230] Z. Huang, W. Dong, L. Ji, C. He, H. Duan, Incorporating comorbidities into latent treatment pattern mining for clinical pathways, Journal of Biomedical Informatics 59 (2016) 227–239.
- [231] M. Lang, T. Bürkle, S. Laumann, H.-U. Prokosch, Process mining for clinical workflows: challenges and current limitations., in: EHealth beyond the horizon: get it there: proceedings of MIE2008 the XXIst international congress of the european federation for medical informatics, 2008, pp. 229–234.

- [232] L. Măruşter, R. J. Jorna, From data to knowledge: A method for modeling hospital logistic processes, IEEE Transactions on information technology in biomedicine 9 (2) (2005) 248–255.
- [233] A. Orellana García, D. Pérez Alfonso, O. U. Larrea Armenteros, Analysis of hospital processes with process mining techniques, in: MEDINFO 2015: eHealth-enabled Health, IOS Press, 2015, pp. 310–314.
- [234] M. Prodel, V. Augusto, X. Xie, B. Jouaneton, L. Lamarsalle, Stochastic Simulation of Clinical Pathways from Raw Health Databases, in: 13th IEEE Conference on Automation Science and Engineering, IEEE International Conference on Automation Science and Engineering, IEEE, 2017, pp. 580–585.
- [235] S. Chen, S. Yang, M. Zhou, R. Burd, I. Marsic, Process-Oriented Iterative Multiple Alignment for Medical Process Mining, in: IEEE International Conference on Data Mining Workshops, 2017, pp. 438–445.
- [236] S. Yang, W. Ni, X. Dong, S. Chen, R. A. Farneth, A. Sarcevic, I. Marsic, R. S. Burd, Intention Mining in Medical Process: A Case Study in Trauma Resuscitation, in: IEEE International Conference on Healthcare Informatics, 2018, pp. 36–43.
- [237] X. Xu, T. Jin, Z. Wei, J. Wang, Incorporating Topic Assignment Constraint and Topic Correlation Limitation into Clinical Goal Discovering for Clinical Pathway Mining., Journal of healthcare engineering 2017 (2017) 5208072.

- [238] S. Yang, J. Li, X. Tang, S. Chen, I. Marsic, R. S. Burd, Process Mining for Trauma Resuscitation., The IEEE intelligent informatics bulletin 18 (1) (2017) 15–19.
- [239] W. Zhou, S. Piramuthu, Framework, strategy and evaluation of health care processes with rfid, Decision Support Systems 50 (1) (2010) 222– 233.
- [240] E. Gattnar, O. Ekinci, V. Detschew, Clinical process modeling and performance measurement in hospitals, in: IEEE 15th International Enterprise Distributed Object Computing Conference Workshops, 2011, pp. 132–140.
- [241] H. Darabi, W. L. Galanter, J.-Y. Lin, U. Buy, R. Sampath, Modeling and integration of hospital information systems with petri nets, in: International Conference on Service Operations, Logistics and Informatics, 2009, pp. 190–195.
- [242] C. Fernandez-Llatas, J. Miguel Garcia-Gomez, J. Vicente, J. Carlos Naranjo, M. Robles, J. Miguel Benedi, V. Traver, Behaviour patterns detection for persuasive design in Nursing Homes to help dementia patients, in: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE Engineering in Medicine and Biology Society Conference Proceedings, IEEE, 2011, pp. 6413–6417.
- [243] J. T. Matamalas, A. Arenas, A. Martinez-Balleste, A. Solanas, C. Alonso-Villaverde, S. Gomez, Revealing cause-effect relations in comorbidities analysis using process mining and tensor network decom-

position, in: 9th International Conference on Information, Intelligence, Systems and Applications, International Conference Information Intelligence Systems and Applications, IEEE, 2018, pp. 329–333.

- [244] M. Zayoud, S. Ionescu, Improving healthcare industry using mining techniques, UPB Science Bulletin 82 (1) (2020) 299–310.
- [245] J. G. Quinn, D. M. Conrad, C. K. Cheng, Process mining is an underutilized clinical research tool in transfusion medicine., Transfusion 57 (3) (2017) 501–503.
- [246] B. Tibeme, H. Shahriar, C. Zhang, Process Mining Algorithms for Clinical Workflow Analysis, in: SoutheastCon 2018, 2018, pp. 1–6.
- [247] L. Canensi, G. Leonardi, S. Montani, P. Terenziani, Multi-level Interactive Medical Process Mining, in: J. H. TenTeije C and Holmes L, A and Popow, Sacchi (Eds.), Lecture Notes in Computer Science, Vol. 10259 of Lecture Notes in Artificial Intelligence, Springer, 2017, pp. 256–260.
- [248] L. Canensi, G. Leonardi, S. Montani, P. Terenziani, A context-aware miner for medical processes, Journal of e-Learning and Knowledge Society 14 (1) (2018) 33–44.
- [249] F. Caron, J. Vanthienen, K. Vanhaecht, E. Van Limbergen, J. Deweerdt, B. Baesens, A process mining-based investigation of adverse events in care processes., Health Information Management Journal 43 (1) (2014) 16–25.

- [250] Y. Chen, W. Xie, C. A. Gunter, D. Liebovitz, S. Mehrotra, H. Zhang, B. Malin, Inferring Clinical Workflow Efficiency via Electronic Medical Record Utilization, in: AMIA annual symposium proceedings, Vol. 2015, 2015, pp. 416–425.
- [251] S. Dahlin, H. Eriksson, H. Raharjo, Process Mining for Quality Improvement: Propositions for Practice and Research., Quality Management in Healthcare 28 (1) (2019) 8–14.
- [252] L. Elezabeth, V. P. Mishra, J. Dsouza, The Role of Big Data Mining in Healthcare Applications, in: 7th International Conference on Reliability, Infocom Technologies and Optimization: Trends and Future Directions, International Conference on Reliability Infocom Technologies and Optimization Trends and Future Directions, IEEE, 2018, pp. 256–260.
- [253] T. Erdogan, A. Tarhan, Process Mining for Healthcare Process Analytics, in: J. Heidrich F, Vogelezang (Eds.), Joint Conference of the International Workshop on Software Measurement and the International Conference on Software Process and Product Measurement, IEEE, 2016, pp. 125–130.
- [254] K. Ganesha, R. Nagaraj, M. D. Nayana, Health care analysis for process deviation using alpha-fitness algorithm in process mining, Journal of Theoretical and Applied Information Technology 88 (3) (2016) 511– 516.
- [255] R. Gatta, M. Vallati, C. Fernandez-Llatas, A. Martinez-Millana,

S. Orini, L. Sacchi, J. Lenkowicz, M. Marcos, J. Munoz-Gama, M. A. Cuendet, B. de Bari, L. Marco-Ruiz, A. Stefanini, Z. Valero-Ramon,
O. Michielin, T. Lapinskas, A. Montvila, N. Martin, E. Tavazzi,
M. Castellano, What Role Can Process Mining Play in Recurrent Clinical Guidelines Issues? A Position Paper., International Journal of Environmental Research and Public Health 17 (18) (2020) 6616.

- [256] R. Gatta, M. Vallati, J. Lenkowicz, C. Masciocchi, F. Cellini, L. Boldrini, C. F. Llatas, V. Valentini, A. Damiani, On the feasibility of distributed process mining in healthcare, in: International Conference on Computational Science, Springer, 2019, pp. 445–452.
- [257] E. Gattnar, O. Ekinci, V. Detschew, Event-based workflow analysis in healthcare, in: Proceedings of the International Joint Workshop on Information Value Management, Future Trends of Model-Driven Development, 2011, pp. 61–70.
- [258] M. Giacalone, C. Cusatelli, V. Santarcangelo, Big Data Compliance for Innovative Clinical Models, Big data research 12 (2018) 35–40.
- [259] C. Guo, J. Chen, Big Data Analytics in Healthcare: Data-Driven Methods for Typical Treatment Pattern Mining, Journal of Systems Science and Systems Engineering 28 (6) (2019) 694–714.
- [260] B. Han, L. Jiang, H. Cai, Abnormal Process Instances Identification Method in Healthcare Environment, in: J. J. Wang SR and Chen K, G and Tate, Sakurai (Eds.), IEEE 10th International Conference on Trust, Security and Privacy in Computing and Communications, IEEE

International Conference on Trust Security and Privacy in Computing and Communications, IEEE COMPUTER SOC, 2011, pp. 1387–1392.

- [261] E. Helm, B. Franz, A. Schuler, O. Krauss, J. Küng, Towards standards based health data extraction facilitating process mining, in: F. M., B. A., L. F., N. V. (Eds.), 6th International Workshop on Innovative Simulation for Health Care, CAL-TEK S.r.l., 2017, pp. 20–25.
- [262] E. Helm, A. M. Lin, D. Baumgartner, A. C. Lin, J. Küng, Towards the Use of Standardized Terms in Clinical Case Studies for Process Mining in Healthcare., International journal of environmental research and public health 17 (4) (2020) 1348.
- [263] E. Helm, J. Küng, Process mining: towards comparability of healthcare processes, in: International Conference on Information Technology in Bio-and Medical Informatics, Springer, 2016, pp. 249–252.
- [264] S. Hirano, S. Tsumoto, Visualizing dynamics of patients in hospitals using devise locations, in: Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics, IEEE International Conference on Systems Man and Cybernetics Conference Proceedings, IEEE, 2014, pp. 2547–2550.
- [265] S. Hirano, S. Tsumoto, Visualization of patient distributions in a hospital based on the clinical actions stored in ehr, in: 2014 IEEE International Conference on Data Mining Workshop, IEEE, 2014, pp. 284–288.

- [266] O. Johnson, General System Theory and the Use of Process Mining to Improve Care Pathways., Studies in health technology and informatics 263 (2019) 11–22.
- [267] X. Li, H. Liu, J. Mei, Y. Yu, G. Xie, Mining Temporal and Data Constraints Associated with Outcomes for Care Pathways, in: Georgiou A., Sarkar I.N., de Azevedo Marques P.M. (Eds.), 15th World Congress on Health and Biomedical Informatics, Vol. 216 of 15th World Congress on Health and Biomedical Informatics, MEDINFO 2015, IOS Press, 2015, pp. 711–715.
- [268] F. Mannhardt, P. J. Toussaint, Revealing Work Practices in Hospitals Using Process Mining., in: MIE, Vol. 247, 2018, pp. 281–285.
- [269] R. S. Mans, W. M. P. van der Aalst, R. J. B. Vanwersch, A. J. Moleman, Process mining in healthcare: Data challenges when answering frequently posed questions, in: Process Support and Knowledge Representation in Health Care, Springer, 2013, pp. 140–153.
- [270] E. Oro, M. Ruffolo, Towards a semantic system for managing clinical processes, in: J. Cordeiro J, Filipe (Eds.), 11th International Conference on Enterprise Information Systems, INSTICC-INST SYST TECHNOLOGIES INFORMATION CONTROL & COMMUNICA-TION, 2009, pp. 180–187.
- [271] S. Quaglin, Information and communication technology for process management in healthcare: a contribution to change the culture of

blame, Journal of Software Maintenance and Evolution: Research and Practice 22 (6-7) (2010) 435–448.

- [272] E. Rojas, M. Arias, M. Sepúlveda, Clinical processes and its data, what can we do with them?, in: F. A. Verdier C. Bienkiewicz M. Gamboa H., Elias D (Ed.), 8th International Conference on Health Informatics, Proceedings; Part of 8th International Joint Conference on Biomedical Engineering Systems and Technologies, SciTePress, 2015, pp. 642–647.
- [273] S. Santhoshkumar, A. Thasil Mohamed, E. Ramaraj, Process analytics model for health care using iot and big data techniques, International Journal on Emerging Technologies 10 (4) (2019) 197–200.
- [274] M. Vitali, B. Pernici, Interconnecting Processes through IoT in a Health-Care Scenario, in: IEEE 2nd International Smart Cities Conference: Improving the Citizens Quality of Life, IEEE, 2016, pp. 164–169.
- [275] T. Vogelgesang, H.-J. Appelrath, Multidimensional process mining: A flexible analysis approach for health services research, in: ACM International Conference Proceeding Series, 2013, pp. 17–22.
- [276] W. Yang, Q. Su, Process mining for clinical pathway: Literature review and future directions, in: 2014 11th International Conference on Service Systems and Service Management (ICSSSM), IEEE, 2014, pp. 1–5.
- [277] C. Yongzhong, Z. Junwu, G. Yalu, S. Chen, Process mining-based medical program evolution, Computers & Electrical Engineering 68 (2018) 204–214.

[278] M. Zayoud, Y. Kotb, S. Ionescu, beta Algorithm: A New Probabilistic Process Learning Approach for Big Data in Healthcare, IEEE Access 7 (2019) 78842–78869.