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

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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

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**	**Transaction type**	**Resource**	...
...	...	...	...	...	...
5302	23/08/2021 08:51:33	Registration	Start	Receptionist Monica	...
5295	23/08/2021 08:53:12	CT scan available	Complete	Radiologist David	...
5303	23/08/2021 08:54:36	Registration	Start	Receptionist Michael	...
5302	23/08/2021 08:55:01	Registration	Complete	Receptionist Monica	...
5301	23/08/2021 08:58:19	EEG test	Complete	Lab technician Jennifer	...
5302	23/08/2021 09:02:46	Consultation	Start	Neurologist William	...
5303	23/08/2021 09:03:25	Registration	Complete	Receptionist Michael	...
5301	23/08/2021 09:07:59	Consultation	Start	Neurologist Amy	...
5292	23/08/2021 09:08:12	Urine test	Complete	Nurse Robert	...
5303	23/08/2021 09:10:53	EEG test	Start	Lab technician Jennifer	...
5287	23/08/2021 09:14:49	Discharge	Start	Neurologist Lisa	...
...	...	...	...	...	...

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

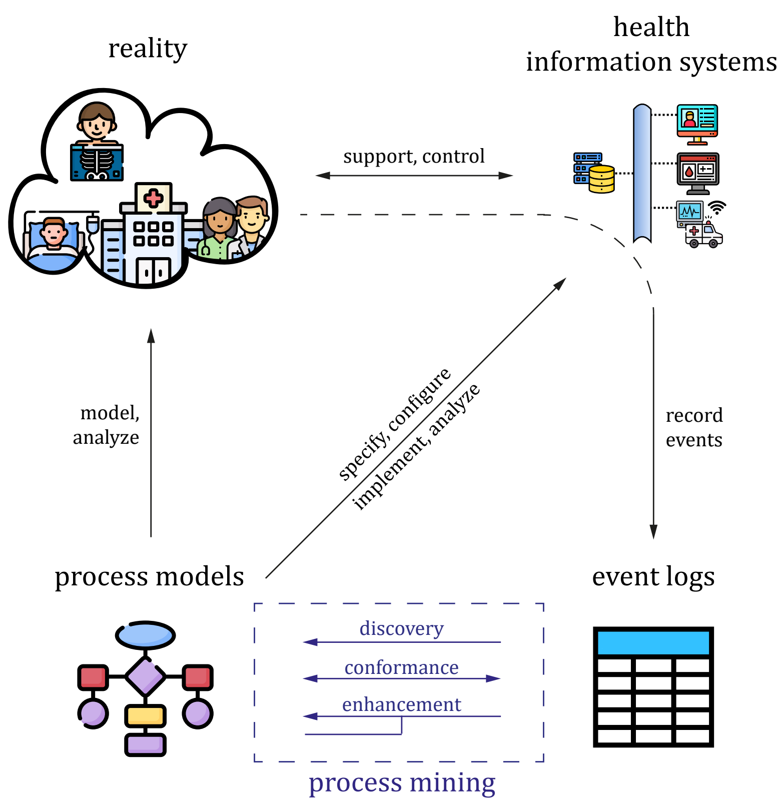

Figure 1: Positioning process mining in healthcare (based on [2, 4, 15]).

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	○	●	●	●	○	●	○	●	○	○	●
Process mining types	○	●	○	●	●	●	○	○	○	●	●
Process mining perspectives	○	●	●	●	○	●	○	○	○	○	●
Process mining algorithms used	●	○	●	●	●	●	○	○	○	●	●
Process mining project stages	○	○	○	○	○	○	○	○	○	○	●
Involvement of domain expertise	○	○	○	○	○	◐	○	◐	○	○	●
KPI	○	○	○	●	○	○	○	○	○	○	●
Time trends											
Number of publications	●	●	○	○	●	●	○	○	●	●	●
Review dimensions	○	○	○	○	◐	○	○	○	◐	○	●

Table 2: Comparison of this review to prior domain literature reviews. ● Yes, included as a review dimension in the review. ◐ Briefly mentioned, but not included as a review dimension. ○ 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-

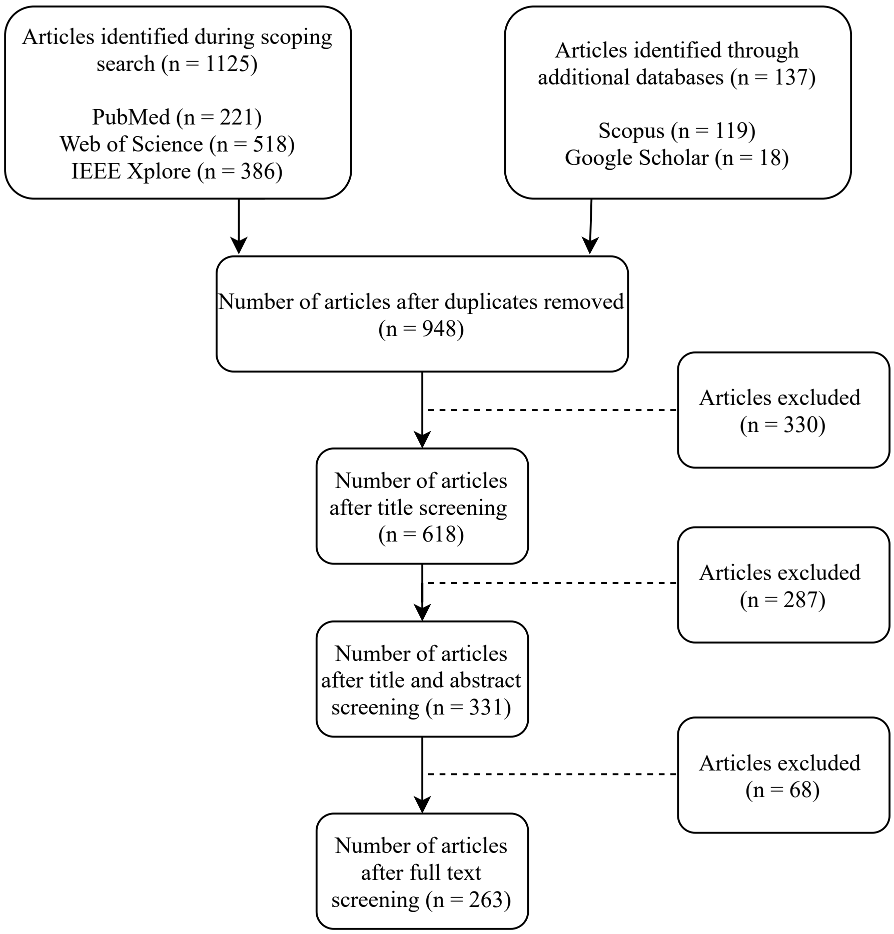

Figure 2: Search strategy.

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.

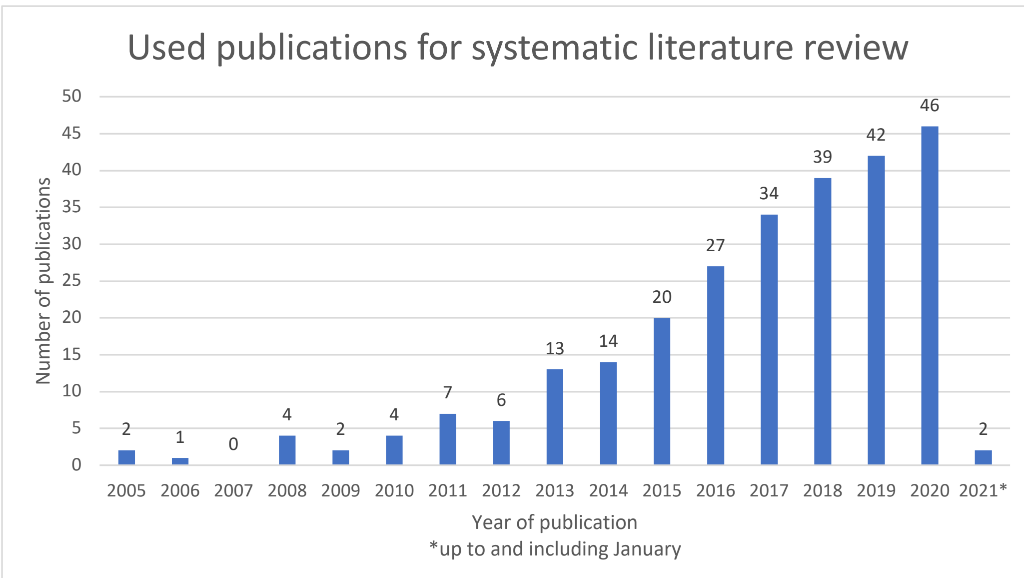

Figure 3: Used publications for systematic literature review.

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 control-flow 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 control-flow perspective is the paper of Lamine et al. [55] who discover the control-flow 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 techniques*. 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.

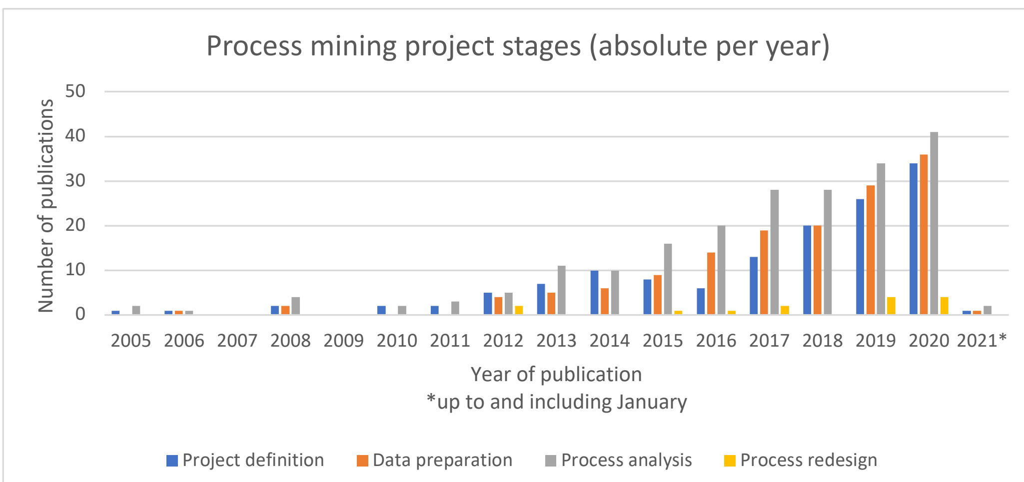

Figure 4: Process mining project stages absolute per year.

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-

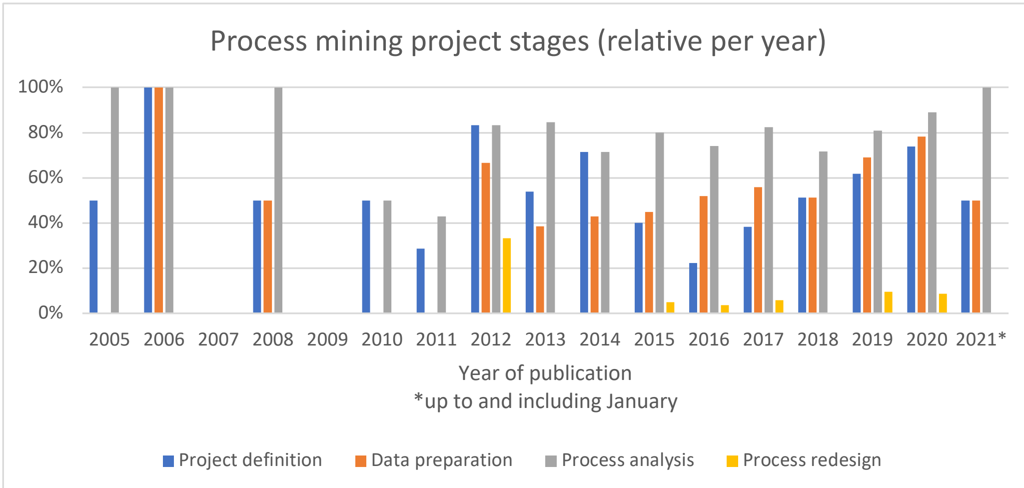

Figure 5: Process mining project stages relative per year.

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.

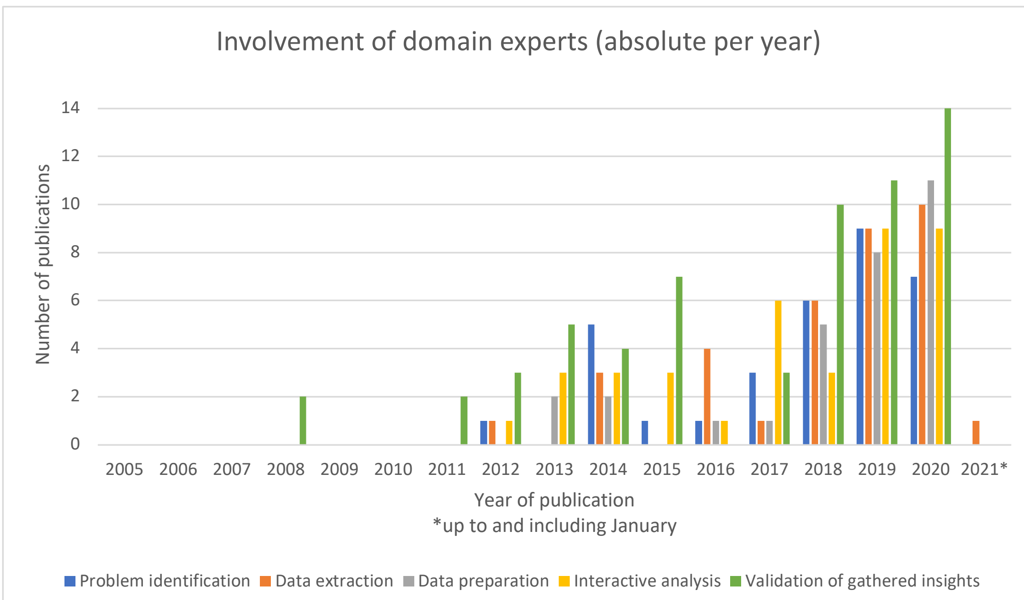

Figure 6: Involvement of domain experts absolute per year.

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

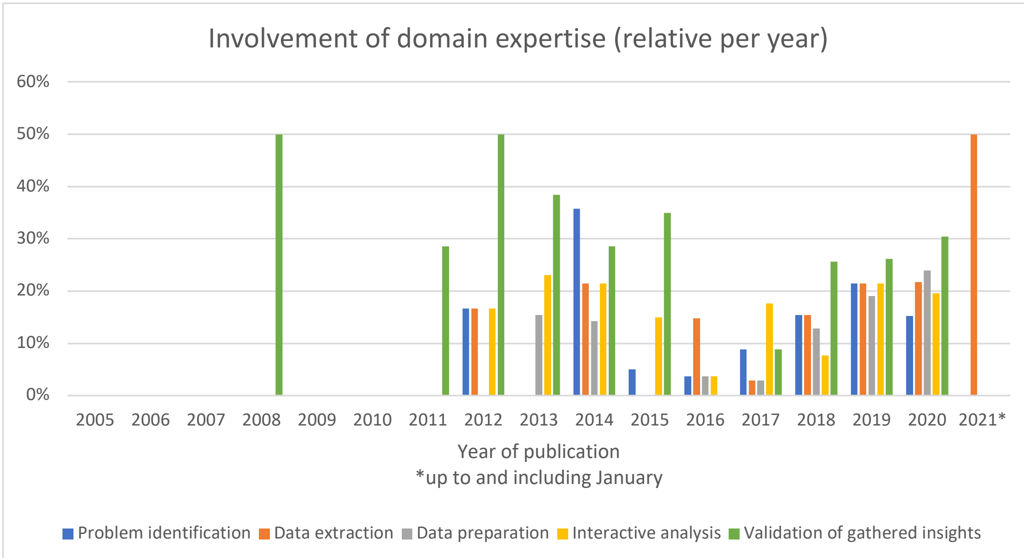

Figure 7: Involvement of domain expert relative per year.

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], door-to-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.

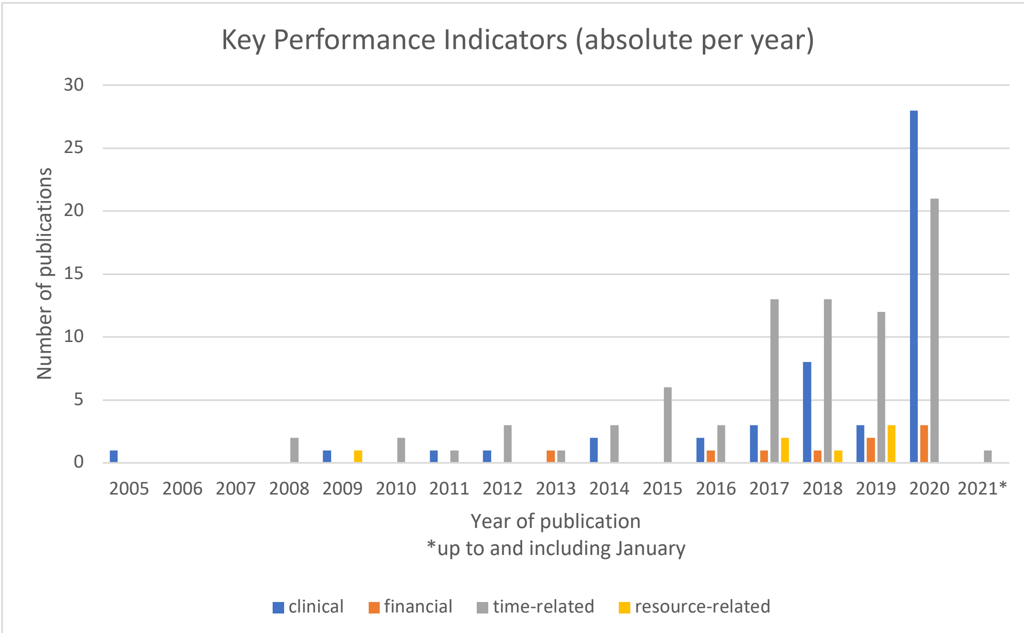

Figure 8: Key Performance Indicators absolute per year.

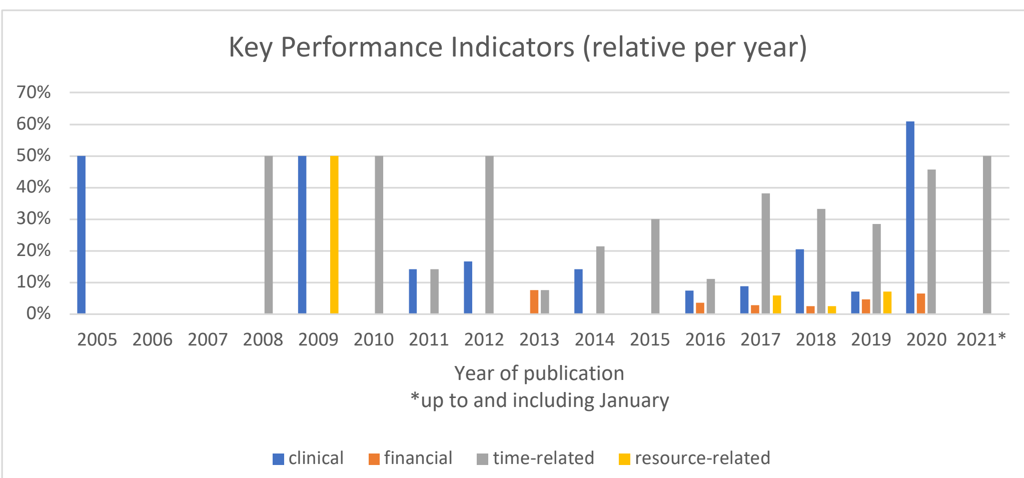

Figure 9: Key Performance Indicators relative per year.

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 A. 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, 45–47, 49, 51–53, 55, 56, 58–66, 68, 69, 72, 74, 76–83, 86, 89–92, 94–96, 98, 99, 101–104, 106, 108, 111–115, 118–165, 165–191]
Data preparation	[5, 9, 27, 29, 30, 34–36, 38–42, 44, 45, 47, 50–57, 59–62, 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, 192–218]
Process analysis	[5, 7, 9, 27–90, 92–116, 118–128, 130–140, 142–145, 147–165, 167–195, 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, 63–65, 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

Appendix C. Papers classified according to the KPIs

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]

Table C.3: Papers classified according to the KPIs

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