ISSN 2278-3091
Volume 9, No.4, July – August 2020
International Journal of Advanced Trends in Computer Science and Engineering
Available Online at http://www.warse.org/IJATCSE/static/pdf/file/ijatcse141942020.pdf
https://doi.org/10.30534/ijatcse/2020/141942020

Challenges and Use Cases of Process Discovery in Process Mining

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ABSTRACT

To date, the amount of data collected are significant and the growth is exponential in various fields over the last decades. Most companies typically address the issue of storage system capacities and therefore such situation creates the issue handling "big data." However, most companies sometimes may find it a challenge to obtain useful knowledge from a large amount of information. As such, numerous organizations are expected to tackle the data-related difficulties. In contrast, there is a necessity to improve and support business processes in progressively changing conditions. Generally, it is possible to analyses the available data and propose improvements because some tools and methods exist to facilitate such cause. Process mining may offer effective approaches to complement the business process. Process mining allows organizations to take advantage of the information within the systems, but can also be used to check process conformance, predict execution challenges, and identify bottlenecks. For instance, healthcare has rapidly changed over decades of research and development. Through scientific discovery, more diseases can be treated. However, it also affects the feasibility of health institutions to accommodate more complicated health treatment processes and systems effectively. Indeed, many solutions exist to cure a particular disease, since machines are becoming further complex, requiring medical staff to be equipped with necessary training. Also, it significantly increases the cost of health care. This paper presents the insights of process mining, highlighting the possible approaches used to gather and analyses the data using feasible method in process mining including real discovery processes. The paper also discusses the challenges of process mining.

Key words: Process Mining, Data Analysis, Process Mining Challenges, Event logs, Process Mining Approaches, Process Discovery.

1. INTRODUCTION

Data analysis area is the future of information technology; however, many existing organizations rely on statistics only to expand the organizational survival [1]. Process mining provides an essential approach for analyzing the data to discover business process. Process mining explores the discrepancy between data of events and models of processes to detect anomalies, compliance checks, predicts delays, facilitates decision-making, and suggest process redesigns [1], [2].

Many industries currently seek new technologies and innovative approaches for improving organizational capabilities [3], [4]. Process mining may be employed, which can process models by applying the technique to a dataset. A model explains the deviation from the actual process, and it can also be used to evaluate the process, to clarify the deviations and the bottleneck. Process mining has been used in numerous case studies within the healthcare context, with promising results.

The delivery of quality healthcare facilities relies on procedures being correctly implemented. Healthcare procedures are a set of interventions aimed at treating, diagnosing, and avoiding any illness to improve the health of an individual. Such procedures are accompanied by clinical and non-clinical operations, carried out by various types of medical staff e.g. physicians, nurses, dentists, clerks, and can vary among medical institutions [5], [6], [7]. The use of process mining techniques in healthcare systems offers a complete insight of the system and complement productivity benefits [5]. In addition, process mining can boost the quality of the facilities rendered and have a positive effect on the management of medical centers. However, one of the main challenges of is the personalization of healthcare processes [8], [9]. The efficiency of healthcare systems can be enhanced by modification of few defensible characteristics including time and cost reduction without compromising the service quality.

In addition, digital records of medical data have enabled a significant logs or data to be collected [2], [10]. Such approach led to understandings of daily operations and offer numerous operational awareness of healthcare processes. First, it enables researchers to understand the process streams. Some of the concerns include what is the pathway that 80% or more of patients follow the process or in which order the process is handled [11]. Furthermore, process mining may identify anomalies within the healthcare process when benchmarked with policy set by the organization [12]. Second, process mining can provide insights into waiting times and process performance, e.g., determination of activities that affect the patients waiting time, leading to high delay [13]. Third, a mechanism exists that enables checking the conformance of the data with a set of rules and guidelines [14], e.g., feasibility to complete activity Aa only after test Tt. Process mining can also indicate the number of cases, which comply with clinical guidelines. Fourth, process mining can be used to determine resources used in a process [12], [15], e.g., when particular resources are available or often what resources have been overloaded. Intrinsically, process mining connects data science, i.e., statistics, machine learning, data mining, and interactive visualization with business process management (BPM) [16].

This paper discusses the overview of process mining. Section 2 presents an overview and use cases of process mining. The summary of event logs is discussed in Section 3. Process discovery is discussed in section 4. The significant challenges to applying process mining are presented in Section 5. Section 6 elaborates on the goals and evaluation of process mining. Tools are discussed in section 7, and at the end concludes the paper.

2. PROCESS MINING OVERVIEW

2.1. Basic Concepts of Process Mining

Modern process mining modelling techniques are usually used to extract information from event logs accessible in the data systems [2], [5]. Process mining is a data-centric and data-driven community [1]. Processing a number of models of event data gives a wide range of compliance inquiries that can be addressed. Process Mining is a technique used to mine genuine process models from event logs to invoke deviations and bottlenecks [17].

When using process mining procedures in healthcare systems, some existing method may not be efficiently employed despite the ability to yield process-efficiency [18]. Nonetheless, process mining can discover the workflows of the enterprise, activity actions, and the mechanism of machines. Therefore, process mining aims at optimizing the business process by offering the abstraction of organizational process, performance, and [16] cultural knowledge. In addition, process mining may allow the identification or diagnosis of fact-based problems [8]. Process mining explores the discrepancy between data of events (observed behavior) and models of processes to detect anomalies, compliance checks, predicts delays, facilitates decision-making, and suggest process redesigns. There are three types of process mining, as shown in Figure 1.

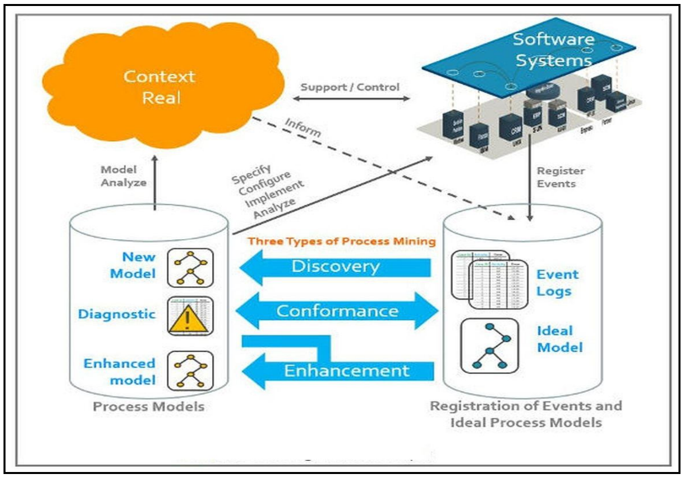


Figure 1: Basic types of Process Mining [16]

2.2. Types of Process Mining

The three techniques of process mining is subsequently discussed.

A. Discovery

The first form of process mining consists of event logging method by a process model with no specific knowledge [19]. The discovery technique incorporates an event log and offers various types of a model of the process. In order to discover the control-flow perspective, several methods have been developed, such as the inductive miner which practices event logs and produces a process model, i.e., a Petri nets clarifying the behavior recorded in the log.

B. Conformance

The second type of process mining technique consists of a process model, which is associated with an event log record. The conformance technique is mainly used to check the authenticity fit in model [2], [5], [18] e.g., the order for the identification of stroke patients as specified in the Medical Standard Protocols. The medical procedures are the experimental check, the brain scan, and the crucial procedure that is necessary to be performed despite the fact that all necessary procedures might not be performed. Conformance checking ensures all the procedures by identifying errors from this workflow in order to identify and explain these errors.

C. Enhancement

Enhancement is used to improve an existing process model with using information about the real process stored in the systems in the form of an event log [20], [21]. Therefore, an authentic model is required to enhance the efficiency of the current health care system.

2.3. Process Discovery Use Cases

A single process with its own state space may have different perspectives. An example is a person's homeostatic cycle, which control sleep and nutrition [22], [23].

The two main drivers in process mining:

1. The business processes in dynamic and rapidly evolving environments need to be strengthened and supported.
2. Events are documented, offering detailed knowledge on the history of the process.

There are numerous analytical directions, and essential questions pointed out in the Table 1 that process mining can answer.

Table 1: Process Mining use cases

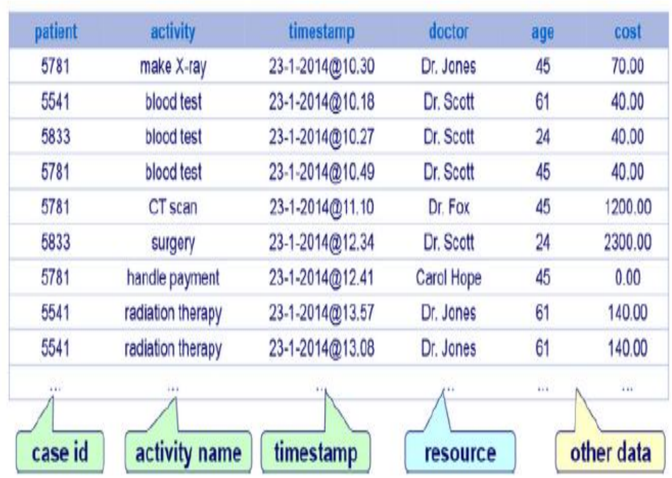
No.	Use Case	Questions	Outcomes
1	Searching for bottlenecks in business processes	Where are the positions that restrict its overall speed of implementation in the process? What is going on behind those sites?	productivity
2	Search for quick/short cuts in business process execution	How to accomplish the fastest process? How do I perform the least number of steps in a process?	productivity
3	Identification of real-world business process	What was the process (except not in words, and not in theory) that describes current activities?	Coherence
4	Detection of deviations in business processes	Where does the method itself deviate from the intended (ideal) phase? Why do these deviations occur?	coherence
5	Prediction of problems in business processes	Can deviations, delays, and risks occurring in process performance be predicted?	Productivity/ coherence

3. EVENT LOG

To implement process mining effectively in the healthcare environment it is crucial to extract the record of all events performed in the system from the records i.e., the information contained in the Electronic Health Records [24].

In healthcare, the process of patient care is known as clinical pathway [25]. It describes a collection of treatment behaviors, along with consultation, tomography, or clinical pathways, with the common objective of treating a patient [26]. A collection of event cases or an activity and timestamps is available. A process model is a conceptual and simplistic way of representing a natural process [27], i.e., a log from an event. It is useful when log data is representative of the model [16], [28], [29]. If event logs are segmented into multiple subgroups and create process models, a detailed models can be obtained [10], [30]. Event logs can be sourced from many resources, such as database system, gateway, network, exchange, ERP, Oracle social media contact log, SAP, open website, or worksheet date. Event logs can express the following content after deleting all the recorded data.

1. **Timestamps -** Log files that are required for each event to be systematic. Particular problems have affected the logging and dates of various clocks.
2. **Correlation -** Event log statistics are available in categories per case; and need association or event-related events to distinguish.
3. **Granularity -** Event enables dissimilar granularity smoother than the behavior applicable to end-users.
4. **Scoping -** Selection from tables that integrate.
5. **Snapshots -** The cases might have a lifetime extending beyond the recorded period.



patient	activity	timestamp	doctor	age	cost
5781	make X-ray	23-1-2014@10.30	Dr. Jones	45	70.00
5541	blood test	23-1-2014@10.18	Dr. Scott	61	40.00
5833	blood test	23-1-2014@10.27	Dr. Scott	24	40.00
5781	blood test	23-1-2014@10.49	Dr. Scott	45	40.00
5781	CT scan	23-1-2014@11.10	Dr. Fox	45	1200.00
5833	surgery	23-1-2014@12.34	Dr. Scott	24	2300.00
5781	handle payment	23-1-2014@12.41	Carol Hope	45	0.00
5541	radiation therapy	23-1-2014@13.57	Dr. Jones	61	140.00
5541	radiation therapy	23-1-2014@13.08	Dr. Jones	61	140.00
...	...	...	...	...	...

Figure 2: Event log example (Selection of attributes depends on the intent of the analysis)

Figure 2 shows, lists of few assumptions regarding event logs:

- A case is made up of events such that each event relates to precisely one case.
- A process consists of cases
- Events can have attributes
- Events within a case are ordered.

Examples of common attribute names are time, activity, costs, and resources.

3.1. Process Mining with Event Logs

As illustrated in Figure 3. Three forms of process mining can be used to extend event logs. The primary method of process mining involves the discovery of pattern with the aid of event logs. A process discovery approach takes an event log as input for knowledge retrieval and generates a scratch model stripped of any prior knowledge/information [31], [32]. Conformance checking is the second type of process mining, where a process model already developed is compared to an event log of a similar process. Conformance methods are used for testing the fidelity of the model as reported in the log and vice versa. Different types of models can be found, i.e., conformance checking can be practical to model procedural models, declarative processes, business rules/policies, laws, and organizational models. Enhancement is the third type of process mining, where the aim is to develop a current model of the process using details about the actual process documented as event logs.

The third form of process mining aims to change or expand the a-priori model [33] by measuring the balance between the fact and the model. In this method, the model is expanded to view throughput times, service levels, bottlenecks, and frequencies using "date or time" timestamps in the event logs.

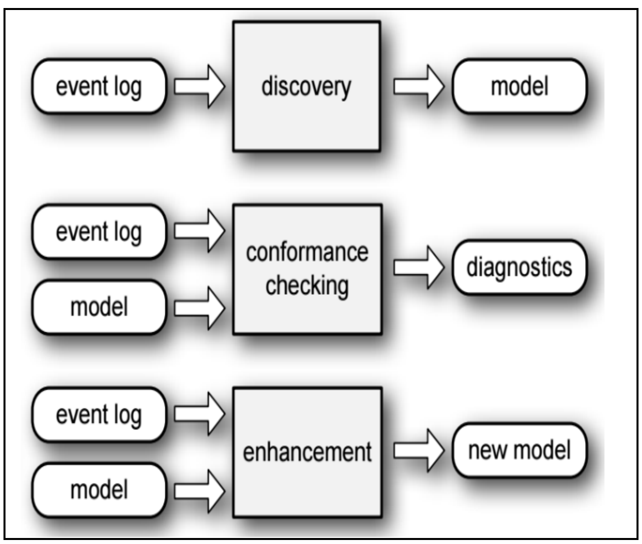


Figure 3: The basic flow of Process Mining

4. PROCESS DISCOVERY

This form of process mining may help to identify an authentic process model. A process model is built based solely on an event log and captures the actions shown in the event log.
Several algorithms typically used for discovery are shown below.

- Multi-phase miner.
- Fuzzy miner.
- Alpha Miner.
- Genetic process mining.
- Heuristic miner.
- Region-based process mining (State-based regions and Language-based regions).
- Alpha+, Alpha++, Alpha#.

In general, "Transition Networks, Workflow Nets, UML, YAWL, BPMN, Petri Nets, Event-Driven Process Chain (EPCs), and Causal Nets (C-Nets)" are widely used.

However, every discovery technique involves some representational bias, which tends to decrease the search space of potential candidate models and can also be used to provide preference to various model types. It is necessary to observe the discovery of processes by definition limited by the expressive capacity of the target language [34]. Hence, representational bias–the objective language used to describe and construct process mining outcomes. Since each notification is not standardized and has its drawbacks e.g., silent measures, working with repetitive tasks, competition, and loops, as well as advantages, using various alternatives may correct process perception.

The principal characteristics of process discovery algorithms are as follows:

1. Direct algorithmic approaches (α -algorithm), two-phase approaches (TS, Markov model $\rightarrow$ WF-net), partial approaches (discovery of frequent episodes, mining of sequent patterns), computational intelligence approaches (neural networks, machine learning, swarm intelligence, genetic algorithm, fuzzy sets, reinforcement learning, rough sets), etc. approaches were used
2. Assumed notion of completeness.
3. Capability to control noise.
4. Representational bias:
   - Unable to represent concurrency
   - Unable to represent duplicate actions
   - Unable to represent hierarchy
   - Unable to represent silent actions
   - Unable to model OR-splits/joins
   - Unable to deal with (arbitrary) loops
   - Unable to represent non-free-choice behavior

5. SIGNIFICANT CHALLENGES OF PROCESS MINING

The process mining pool is concerned with valuable harvesting information regarding process execution through analysis of the event logs. Process mining is a valuable tool for evaluating event log-based operating process executions [18]. Existing methodologies perform well on standardized processes, but issues persist with the exploration and simulation of less structured data. The problem of complexity, i.e., whether a set of events are organized differently, evidently increases with the number of situations being examined [35]. Processes comprise an unspecified number of components of process instance, each referring to an event, i.e., a particular process execution.

Mining processes can produce various insights into the workings of healthcare processes:

1. Checking data compliance with a set of rules and regulations: for instance, does operation O is only conducted after completing the test T? In many cases, will the guidelines work accordingly?
2. In what way resources work inside a process: e.g., which sometimes overwork among them, or when particular resources are involved?
3. Insights into waiting times and productivity of processes: e.g., between which tasks patients expect the lengthiest in a given phase?
4. System flow insights: e.g., what is the direction taken by 80% of the patients? The provision of these insights supports to discover the 'key' practice and to identify anomalies, mainly because healthcare processes are partly organized with many exceptions.

A few significant challenges of process mining have been listed in the following Table 2.

Table 2: Some of the most important challenges of process mining [2], [33]

Challenges of Process Mining	
Challenge	**Description**
Dealing with Complex Event Logs in Process Exploration with diverse characteristics.	Event logs can be very different in formats. Some event logs can be massive, making them difficult to manage, while other event logs are so small that not enough information is available to draw accurate conclusions.
Balancing For process discovery between performance parameters.	The challenge is to find models in all four dimensions that score well. There are four dimensions of competing performance: (a) simplicity; (b) precision; (c) fitness; and (d) generalization.
Providing Working Support for process discovery.	Process mining is not limited to off-line research; it can also be used to support operations online. There are three recognizable organizational support activities: predict, detect, and suggest.
Refining Usability for Non-experts to Discover Process Model.	The challenge is to cover underneath user-friendly interfaces the sophisticated process mining algorithms, which set parameters automatically and recommend suitable analytical styles.
Cleaning, Merging, and Finding Event Data for Process Discovery.	Many problems need to be addressed when collecting event data appropriate for process mining. Data may be distributed through several sources; event data may be incomplete, logs may contain events at a specific level of granularity, an event log may include outliers, etc.
Creating Representative Benchmarks to Discover Process Model.	The comparison and enhancement of the different tools and algorithms include clear metrics consisting of example data sets and representative quality criteria.
Improving Representative Bias used to discover the process.	For ensuring high-quality process mining performance, more detailed and accurate selection of the representational bias is required.
Cross-Organizational mining for discovery.	There are various application scenarios where multi-organization event logs are accessible for analysis. Many organizations work together to manage process instances or organizations effectively conduct a similar process while exchanging experiences, information, or shared infrastructure. Traditional process mining techniques, however, usually find one event log within an organization.
Combining process mining method with further analysis forms.	The challenge is to integrate automated process mining approaches with many new approaches to analysis (simulation, data mining, optimization techniques, visual analytics, etc.) in order to gain more information from event results.
Refining understandability for Non-experts to Discover Process Model.	The recipient may have difficulties understanding the performance or may be inclined to draw wrong conclusions. The trustworthiness of the outcomes should always be indicated, and the findings should be presented using an acceptable representation to prevent these issues.

6. EVALUATION AND GOALS OF PROCESS MINING

In a nutshell, process mining benefits in the optimization of the management of medical care by highlighting vulnerabilities and cost generators in hospital management systems, and also allows patients and hospital staff to focus on what is acute "Treatment and Recovery."

Evaluations-

- Evaluation of clinical pathways/patient treatment journeys (transfers, referrals) through the hospital.
- Evaluation of the allocation flow of medical personnel to various wards (to support resource planning and uncover staff issues.
- Evaluation of the compliance of the healthcare process flows to normative guidelines.

Goals-

- To discover and visualize clinical pathways (patient journeys) for patients in specific pathology clusters.
- To quantify most/least common pathways and associated time delays.
- To quantify the difference between the journeys of patients undergoing only lab tests, versus patients undergoing lab tests and the recommended surgical procedures.

7. TOOLS

Tool like ProM, all the techniques mentioned above have been realized. ProM is an extensible platform in the form of plug-ins that supports an extensive range of process mining approaches [36], [37].

ProM software has the following characteristics:

- The objective is to cover the full range of process mining spectrum.
- Many plug-ins are experimental and not user-friendly prototypes.
- Also, facilitate operational support and conformance checking.
- Supported notations: Petri Nets (many types), Fuzzy Models, Switch Systems, C-Nets, BPMN, Declare, etc.

This instrument is incredibly dominant but unsatisfying for someone. There are previously 600 plug-ins, and that number is increasing.

Disco commercial software has the following characteristics:

- Easy to use and exceptional performance.
- It does not facilitate conformance checking and organizational support.
- Uses a Fuzzy model variant.
- Strong filtering capabilities for comparative mining processes and ad hoc pattern checks.
- Emphasis on the study of discovery and performance (including the animation).

Disco tool provides easy to use interface, and intuitive to users and as such, might be operated by inexperienced users.

To implement process mining many existing tools are available as shown in Figure 4, but there is still a relatively new discipline in process mining. Over the coming years, new technologies will emerge, and more business intelligence/business process models/data mining packages will include process mining functionality.

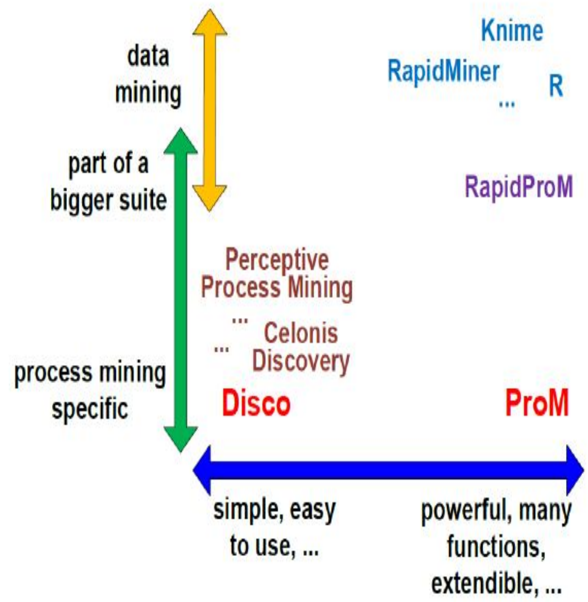


Figure 4: Process Mining tools spectrum [38]

Standard tools for process mining with specifying benefits and disadvantages listed in Table 3.

Table 3: Example of Process Mining products

Tool	Advantages	Disadvantages
Disco	Support seamless abstraction and generalization of cartography, emphasis on high performance, have Nitro capable of recognizing different time formats, dealing with complex (Spaghetti-like)	No auto-discovery (API based), additional attribute filtering is missing.

	processes, and mapping them automatically to MXML or XES notation algorithms based on fuzzy mining.	
InterStage BPME	Wanting not to install, be able to seamlessly separate from unusual actions, emphasis on process discovery, capable of measuring output using indicators such as flow time.	Unsupported prediction. Unable to identify concurrency, conformance checking and recommendations.
Reflect|One	Supported scalability, BPM life cycle, reflect user-friendliness, social networking support for organizational mining, Discovery algorithms: on a sequential model, on genetic mining.	Conformance checking and prediction not supported.
Enterprise Visualization Suite	Concentrate on evaluating business processes assisted by SAP. α-algorithm-inspired process discovery algorithm and heuristic mining.	High Cost, poor BI capabilities, Embedment Issues.
ARIS Process Performance Manager	Emphasis on performance analysis (instance level drilling, benchmarking, dashboards), help an organization's mining.	Not support prediction, recommendation and conformance checking.
Service Mosaic	Service interaction log analyses discover transition mechanisms, focuses on resolving noise and protocol refinement.	Unable to discover concurrency

8.CONCLUSION

In conclusion, process mining helps experts consider the real implementation of the processes: developing process models, evaluating professional-quality enforcement, and identifying opportunities for change. The technique allows the creation of a model based on event logs. In addition, process mining techniques is capable to offer improved insights into how processes are being conducted in real life. Process mining provides many contributions in many domains and healthcare in one of the popular domains in Process Mining. Healthcare event logs are used for process analyses, which can help authorities in many cases. This paper presents an overview of process mining and the main approaches used to implement process mining. It includes an understanding of process mining, event log, goal and challenges, pros and cons, description of the process, data types, and tools. A combination of process mining techniques, text, data, and are used to distinguish and assess diversity inpatient structure, flow, and many real process problems.

REFERENCES

[1] S. Park and Y. S. Kang, "**A Study of Process Mining-based Business Process Innovation**," *Procedia Comput. Sci.*, vol. 91, no. Itqm, pp. 734–743, 2016. https://doi.org/10.1016/j.procs.2016.07.066

[2] W. Van Der Aalst *et al.*, "**Process Mining Manifesto**," pp. 169–194, 2012.

[3] Z. He, Q. Wu, L. Wen, and G. Fu, "**A process mining approach to improve emergency rescue processes of fatal gas explosion accidents in Chinese coal mines**," *Saf. Sci.*, vol. 111, no. July 2018, pp. 154–166, 2019.

[4] M. Werner, "**International Journal of Accounting Information Systems Financial process mining - Accounting data structure dependent control fl ow inference**," *Int. J. Account. Inf. Syst.*, vol. 25, no. February, pp. 57–80, 2017.

[5] E. Rojas, J. Munoz-Gama, M. Sepúlveda, and D. Capurro, "**Process mining in healthcare: A literature review**," *J. Biomed. Inform.*, vol. 61, pp. 224–236, 2016.

[6] R. S. Mans, W. M. P. Van Der Aalst, and R. J. B. Vanwersch, ***Process Mining in Healthcare Evaluating and Exploiting Operational Healthcare Processes***. 2015.

[7] H. P., "**Process mining challenges in hospital information systems**," *2012 Fed. Conf. Comput. Sci. Inf. Syst. FedCSIS 2012*, 2012.

[8] M. Prodel, V. Augusto, X. Xie, B. Jouaneton, and L. Lamarsalle, "**Discovery of patient pathways from a national hospital database using Process Mining and Integer Linear Programming**," *2015 IEEE Int. Conf. Autom. Sci. Eng.*, pp. 1409–1414, 2015. https://doi.org/10.1109/CoASE.2015.7294295

[9] S. V. Kovalchuk, A. A. Funkner, O. G. Metsker, and A. N. Yakovlev, "**Simulation of patient flow in multiple healthcare units using process and data mining techniques for model identification**," *J. Biomed. Inform.*, vol. 82, no. May, pp. 128–142, 2018.

[10] W. M. P. van der A. M. Song, C.W. G¨unther, "**Trace Clustering in Process Mining**." International conference on business process management. Springer, Berlin, Heidelberg.

[11] R. S. Mans, W. M. P. van der Aalst, and R. J. B. Vanwersch, "**Data challenges when answering frequent posed questions**," pp. 140–153, 2015.

[12] J. Lismont, A. Janssens, I. Odnoletkova, F. Caron, and J. Vanthienen, "**A guide for the application of analytics on healthcare processes : A dynamic view on patient pathways**," *Comput. Biol. Med.*, vol. 77, pp. 125–134, 2016.

[13] P. Jaisook and W. Premchaiswadi, "**Time Performance Analysis of Medical Treatment Processes by using Disco**," *2015 13th Int. Conf. ICT Knowl. Eng. (ICT Knowl. Eng. 2015)*, pp. 110–115, 2015.

[14] S. J. J. L. B, D. Fahland, and W. M. P. Van Der Aalst, "**Using Life Cycle Information in Process Discovery**," pp. 204–217, 2016.

[15] F. Fox, "**A Data Quality Framework for Process Mining of Electronic Health Record Data**," *2018 IEEE Int. Conf. Healthc. Informatics*, pp. 12–21, 2018. https://doi.org/10.1109/ICHI.2018.00009

[16] W. M. P. van der Aalst, ***Process Mining: Discovery, Conformance and Enhancement of Business Processes***. 2011.

[17] C. Alvarez *et al.*, "**Discovering role interaction models in the Emergency Room using Process Mining**," *J. Biomed. Inform.*, vol. 78, no. November 2017, pp. 60–77, 2018.

[18] F. Caron, J. Vanthienen, and B. Baesens, "**Healthcare Analytics: Examining the Diagnosis–treatment Cycle**," *Procedia Technol.*, vol. 9, pp. 996–1004, 2013.

[19] C. Diamantini, L. Genga, and D. Potena, "**Behavioral process mining for unstructured processes**," *J. Intell. Inf. Syst.*, pp. 5–32, 2016.

[20] J. Munoz-gama, ***Checking and Diagnosis Comparing Observed and Modeled Processes***. .

[21] D. V. M V Kamal, "**ABPMDF: Towards a Framework for Automated Model Discovery from Process Event Logs for Business Intelligence**," *Int. J. Adv. Trends Comput. Sci. Eng.*, vol. 8, no. 3, 2019. https://doi.org/10.30534/ijatcse/2019/88832019

[22] M. L. V. E. B, N. Sidorova, and W. M. P. Van Der Aalst, "**Discovering and Exploring State-Based Models for Multi-perspective Processes**," pp. 142–157, 2016.

[23] S. Sch, C. Di Ciccio, and F. M. Maggi, "**Discovery of Multi-perspective Declarative Process Models**," vol. 1, pp. 87–103, 2016.

[24] R. Gatta and A. Damiani, "**A Framework for Event Log Generation and Knowledge Representation for Process Mining in Healthcare**," 2018.

[25] M. Prodel, V. Augusto, B. Jouaneton, L. Lamarsalle, and X. Xie, "**Optimal Process Mining for Large and Complex Event Logs**," *IEEE Trans. Autom. Sci. Eng.*, vol. 15, no. 3, pp. 1309–1325, 2018.

[26] Á. Rebuge and D. R. Ferreira, "**Business process analysis in healthcare environments: A methodology based on process mining**," *Inf. Syst.*, 2012.

[27] M. H. B. A. Bakar, S. Ismail, and S. H. S. Ali, "**A process mining approach to understand self regulated-learning in moodle environment**," *Int. J. Adv. Trends in Comput. Sci. Eng.*, vol. 8, no. 1.3 S1, pp. 74–80, 2019. https://doi.org/10.30534/ijatcse/2019/1581.32019

[28] N. Tax, T. Universiteit, N. Sidorova, T. Universiteit, A. Technische, and U. Eindhoven, "**Event Abstraction for Process Mining using Supervised Learning Techniques**," no. June, 2016.

[29] V. Augusto, X. Xie, M. Prodel, B. Jouaneton, and L. Lamarsalle, "**Evaluation of discovered clinical pathways using process mining and joint agent-based discrete-event simulation**," *2016 Winter Simul. Conf.*, pp. 2135–2146, 2016.

[30] P. De Koninck, J. De Weerdt, and S. K. L. M. Broucke, "**Explaining clusterings of process instances**," *Data Min. Knowl. Discov.*, 2016.

[31] F. M. B, M. De Leoni, H. A. Reijers, and W. M. P. Van Der Aalst, "**Data-Driven Process Discovery - Revealing Conditional Infrequent Behavior from Event Logs**," vol. 1, pp. 545–560, 2017.

[32] G. Schuh, J. Prote, M. Luckert, and P. Hünnekes, "**Knowledge discovery approach for automated process planning**," *Procedia CIRP*, vol. 63, pp. 539–544, 2017.

[33] W. I. L. V. A. N. D. E. R. Aalst, "**Process Mining : Overview and Opportunities**," vol. 3, no. 2, pp. 1–17, 2012.

[34] H. M. W. V. B. F. Van Dongen and E. K. C. W. Günther, "**Process mining : a two-step approach to balance between underfitting and overfitting**," pp. 87–111, 2010.

[35] L. George, B. Cadonna, and M. Weidlich, "IL-Miner : **Instance-Level Discovery of Complex Event Patterns**," vol. 10, no. 1, pp. 25–36, 2016.

[36] A. Bolt, M. De Leoni, and W. M. P. Van Der Aalst, "**Scientific workflows for process mining : building blocks , scenarios , and implementation**," *Int. J. Softw. Tools Technol. Transf.*, vol. 18, no. 6, pp. 607–628, 2016.

[37] E. González, L. De Murillas, H. A. Reijers, and W. M. P. Van Der Aalst, "**Connecting databases with process mining : a meta model and toolset**," *Softw. Syst. Model.*, 2018. https://doi.org/10.1007/s10270-018-0664-7

[38] J. Rudnitckaia, "**Process Mining . Data science in action**," University of Technology, Faculty of Information Technology (2016): 1-11.