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A Systematic Literature Review of Studies Comparing Process Mining Tools

Cuma Ali Kesici
Bilkent University, Industrial Engineering Department, 06800, Ankara, Turkey
E-mail: ali.kesici@ug.bilkent.edu.tr

Necmettin Ozkan and Sedat Taşkesenlioglu
Kuveyt Turk Participation Bank, Information Technologies Research and Development Center, 41420, Kocaeli, Turkey
E-mail: {necmettin.ozkan, sedat.taskesenlioglu}@kuveytturk.com.tr

Tugba Gurgen Erdogan
Hacettepe University, Computer Engineering Department, 06800, Ankara, Turkey
E-mail: tugba@cs.hacettepe.edu.tr

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Abstract: Process Mining (PM) and PM tool abilities play a significant role in meeting the needs of organizations in terms of getting benefits from their processes and event data, especially in this digital era. The success of PM initiatives in producing effective and efficient outputs and outcomes that organizations desire is largely dependent on the capabilities of the PM tools. This importance of the tools makes the selection of them for a specific context critical. In the selection process of appropriate tools, a comparison of them can lead organizations to an effective result. In order to meet this need and to give insight to both practitioners and researchers, in our study, we systematically reviewed the literature and elicited the papers that compare PM tools, yielding comprehensive results through a comparison of available PM tools. It specifically delivers tools' comparison frequency, methods and criteria used to compare them, strengths and weaknesses of the compared tools for the selection of appropriate PM tools, and findings related to the identified papers' trends and demographics. Although some articles conduct a comparison for the PM tools, there is a lack of literature reviews on the studies that compare PM tools in the market. As far as we know, this paper presents the first example of a review in literature in this regard.

Index Terms: Process Mining, Disco, ProM, Celonis, Benchmarking.

1. Introduction

Process mining (PM) is an analytical technique relating to the fields of data science and process management for discovering and improving processes. Basis of PM is methods and technologies of business process modelling and data mining. It deals with discovering, monitoring and improving real processes by extracting knowledge from event logs available in information systems [1]. Over the last years, event data has become readily available, PM techniques have matured, and PM algorithms have been implemented in various academic and commercial systems. For instance, as PM can be a bridge between process science and data science, it has become an essential technique for ambitious and fast-growing manufacturing organizations that operate according to Industry 4.0 [2, 3]. Today, PM can be used in all industries like financial services, manufacturing, healthcare and information systems. It is used not only by information technology (IT) professionals, but by many departments in the organizations [4].

PM tools can be used for business process effectiveness at the organization of different industries [5]. In this widespread use of the PM, PM tools' abilities play a significant role. It is difficult to analyze the log files stored in the servers of enterprises without PM tools. The needs of enterprises in terms of the value which they seek in their event data are dependent on the capabilities of the PM tools that they are planning to use during the digital transformation processes. They greatly affect the results of the PM results, the degree of usability of them that are obtained at the end of the process and the process of producing effective and efficient outputs and outcomes that organizations desire. This importance of the tools makes the selection process of the relevant tools critical. In the selection process of appropriate tools, a comparison of them can lead organizations to an effective result.

The criteria of determining the right tool for an enterprise during the PM analysis have been researched by many researchers. The comparisons of the existing PM tools in the market are done under various criteria such as their technical capabilities of process discovery, conformance checking, model enhancement, visual representation of the outputs which contains the valuable information extracted from a given event data, etc. However, although many articles conduct a comparison for the PM tools, in particular, there is a lack of literature reviews on the studies that compare PM tools in the market.

Because there exists no study to review the literature on comparing PM tools, we reviewed the literature and elicited the papers that compare PM tools in the market to guide the potential users of PM tools and relevant academic researchers about choosing the right tool. This study provides a comprehensive result, with the guidance of research questions identify the study, and as far as we know presents the first example in literature as a systematic literature review (SLR) on the studies comparing PM tools. When considering there exist limited studies comparing PM tools, our study aims to review and classify studies that compare PM tools in order to both underline potential gaps for further studies and give insight to both practitioners and researchers. Thus, this research may contribute to the literature by adding to the body of knowledge of the considerable inputs.

The remaining of this article is organized as follows: Section 2 summarized the background on PM and Section 3 explains the secondary studies that reviewed PM studies. Section 4 describes the research design used in this study. Section 5 presents the results in relation to research questions. Section 6 discusses the results and Section 7 concludes the study and states the directions of future work.

2. Background

The main research objective of this study is to investigate the main characteristics of PM tools by reviewing systematically the studies which compare PM tools. With respect to the objectives of study, in this section, we give a broad overview of PM from mostly an industry perspective. After that, we discuss existing PM tools in the industry with some examples.

PM is for the enterprises which have enough data to evaluate further investigations of their processes. Fortunately, with the lead of digital transformation, enterprises can seek a way to explore their processes and the relation among them. The constant increase in the production of data thus opens a gate to handle the problem of dealing with the processes, in more powerfully thanks to the PM capabilities. PM helps enterprises to extract valuable information from a set of events available in the enterprises and gives them an understanding of how their processes behave and further the ability to support business decisions by determining the relation between processes.

According to Tiwari et al. [6], "one of the major drivers behind the rise of business PM is the need for companies to learn more about how their processes operate in the real world". Although the processes may act according to a plan, it does not mean processes cannot tell more than the original plan because there is always an error term caused by the deviation of the plan. Therefore, there is always a need to check how the processes behave in the real world and determine the actions for when the desired plan cannot accrue. Enterprises can then use PM's ability to extract useful information from a given data and explore hidden processes.

PM uses a set of techniques to explore the behaviour of the processes and their relation among them. "The goal of process mining is to automatically produce process models that accurately describe processes by considering only an organization's records of its operational processes" [7]. There are several algorithms for representing the collection of processes as a process model. It is important to notice that there is no algorithm that perfectly creates a process model from the given collection of processes data. The stage of representing the collection of processes as a process model is commonly referred to as the process discovery stage of PM. Process discovery uses algorithms such as α algorithm [8], the inductive miner [9], and the heuristic miner [10]. The usage of each discovery algorithm may result in different final process models. Therefore, there is an additional step required to check the conformance of processes into event log objects. To sum up, the main focus of PM is to discover processes, check conformance of the processes to event log i.e. process model, and enhance the business processes by making a clear understanding of processes [8].

In order to apply the PM techniques into the processes, there are some tools available in the market such as open-source software toolkits and as well as commercial products offered by developers. The commercial products are easier to use than the open-source software toolkits solution [11, 12]. These tools provide user interfaces with features such as filtering data, simulation, and evaluation of process discovery to help users to interact with the event log objects more easily than the open-source software toolkits. The features of these tools allow users to extract knowledge about the processes in an elaborate way. Most of the tools have the main abilities such as process discovery i.e. creating a process model, conformance checking and some of the tools provide the features of simulation of the processes, filtering the event data, rework, noise, and trace deviation explorations. Each tool has various features that satisfy the customer's needs in terms of exploring the processes of an enterprise.

The capabilities of tools have a significant impact on providing insightful information from a given data. In order for these tools to generate valuable information, it is important to create process models from the given event data as correctly as possible, check the conformance of the created process model to the event data, and be available for model enhancement in case of further changes in the event data. Therefore, the importance of these tools is correlated with the capabilities of tools generally such as process discovery, conformance checking, and model enhancement. Any other features in addition to these core features of PM tools are a dependent factor to the specific needs of an enterprise.

3. Related Work

In cases where the number of PM primary studies (e.g., experience reports) in a specific area is rapidly and significantly growing. Several literature reviews have revealed the state of PM applications in specific domains such as healthcare [13], specific techniques [14] or in general [15]. Urrea-Contreras et al. [16] present the results of a SLR that reveals the state of the art of PM perspectives in software engineering. It provides a conceptual definition of PM perspectives, their implementation in case studies, and the successful contributions to the challenges and opportunities of implementing the perspectives identified in the software engineering domain. The study highlights the lack of a standardized definition for the term PM perspective in this domain. Velazquez-Solis et al. [17] provide a SLR on software process improvement projects which help to satisfy the business objectives. Thiede et al. [18] review empirical studies on PM in order to understand its use by organizations. As an implication based on the results, it underlined that PM researchers have paid little attention to utilizing complex scenarios, e.g., cross-system, service, or organizational PM to allow new insights into customer processes by supplying business operations with valuable and detailed information. Ghasemi et al. [19], in their systemic literature review based on 24 papers, highlight that the use of PM in association with the goals of the organizations does not yet have a coherent line of research. However, none of these secondary studies provides a literature review on the comparison of the PM tools.

Recently, organizations try to adapt to the requirements of digital transformation and make the process information useful for process improvement. To do that it is important to interpret the event logs by modeling the processes correctly. PM tools have a significant impact on process discovery, conformance checking, and enhancement. In order to get the most out of the available information, the selection of the right PM tool is significant. Thus, the studies about the comparison of PM tools could be beneficial for organizations and practitioners. Although the studies that are evaluated in the context of this SLR provide a comparison in terms of the prerequisites that are stated in the next section, it is observed that they do not follow a common methodology or approach to compare the PM tools. The need for a common methodology or approach to compare a set of PM tools as a guideline for practitioners to select the right PM tools for their business is stated later in this paper. Drakoulogkonas and Apostolou [20] introduce a multi-criteria methodology for practitioners to compare PM tools. The methodology consists of three different selection methods such as ontology, Analytic Hierarchy Process (AHP), and decision tree and it aims to help users to determine the right tool in terms of their needs. The proposed comparison methodology also provides a set of criteria categorized under four headings such as General, Process Mining Types, Operational Support Activities, and Discovery Problems Addressed. With the categorization of criteria and selection methods, the proposed comparison methodology by Drakoulogkonas and Apostolou aims to fill the gap that is addressed in this paper in discussion section.

4. Research Methodology

The aim of this study is to review the current status of PM tools using a SLR to classify papers, in particular, by concentrating on studies providing any kind of comparisons among the tools. In contrast to an expert review using ad hoc literature selection, SLR is a methodologically rigorous review of research results [21]. Based on this purpose, this research process has been undertaken as a SLR based on the guidelines as proposed by the Kitchenham et al. [21] and the following steps were derived:

- Defining research goals and questions
- Defining search query and searching for papers
- Screening the retrieved papers which results in a set of relevant papers
- Application to inclusion/exclusion criteria
- Quality Assessment
- Data Extraction and SLR

The research process starts with defining research goals and questions and search query. After searching the queries in seven digital libraries, we gathered potentially relevant publications. For screening the retrieved studies, we developed and applied inclusion/exclusion criteria and obtained a final pool of studies. After extracting the data from studies, the results of SLR are analysed. The remainder of the section concerns the research questions, paper selection process, quality assessment, data collection and potential threats to validity.

4.1. Research Questions

The aim of this study, to identify, analyse and synthesize the studies which compare PM tools. Thus, we set the main goals related to our research: 1) identify the studies which compare PM tools 2) analyse and synthesize the studies' results. Based on our study's goal, we raise and investigate four research questions (RQs):

RQ1. Compared PM Tools: Which tools were compared in the studies? Along with the increasing significance PM, many different tools with varying abilities have appeared on the market and continue to emerge. The wide range of tools forces decision makers to choose between them. In this context, it is a matter of curiosity which tools and among them which ones are mostly compared in the academic world, which can be partially isolated from commercial concerns. This comparison aspect can be regarded as a direct or indirect implication of interest in them. To address RQ1, we directly focused on studies comparing PM tools and excluded algorithms used by varying tools. However, being subject of such comparison does not provide an affirmative result for the tools, rather, it is needed to reveal the strengths and weaknesses of them (RQ3 relevantly).

RQ2. Comparison Methods or Criteria: Which methods or criteria were used to compare the tools in the studies? When it comes to RQ2, what criteria the researchers use when comparing the tools and by which methods they compare these criteria are also significant in terms of getting the point of perspectives taken to the tools' comparisons. This matter will hopefully provide a basis for us to compare the perspective of the literature with the point of view of the field and can open gates to further studies if needed. For example, lack of the criteria set taken from perspectives based on human perceptions (such as capability and easiness of the tools' use and development by them) rather than the pure objective characteristics of the tools, is a matter of curiosity and possible further research.

RQ3. What are strengths and weaknesses of the compared tools? The criterion that come into prominence about the comparison tools is what their strengths and weaknesses are. By focusing on this topic, it is aimed to provide an important input to decision makers in their tool selections.

RQ4: Trends and Demographics of the Publications: The following set of sub-questions were formulated by reviewing the existing bibliometrics studies:

- *RQ4.1 Top Venues:* Which venues (journals or conferences) are the main targets of publications?
- *RQ4.2 Top-Cited Publications:* Which publications have been most cited by others?
- *RQ4.3 Publication Count by Year:* What is the yearly number of publications in the field?

4.2. Publication Selection Process

The search process was a manual search of peer-reviewed sources in well-known digital libraries without any specific filter in the year range. The review process was determined iteratively by the first three authors of our study. In the first iteration, to determine the appropriate keywords, a preliminary search was conducted in Google Scholar with the word (Comparative OR Comparing OR Comparison OR Compare) and the first 100 returned results were examined in terms of effectiveness of the search key. We realized that the studies inside the scope may and should include the keyword "benchmark" as well. Then, the "benchmark" keyword was added to our search string. Regarding the search location, we anticipated and were satisfied with the effectiveness of searching in metadata instead of the full text as the main aim of the paper is a comparison of PM tools, then it is expected authors locate the relevant terms that we cover in their papers' metadata. The reason for using two different keywords was that the original keyword we identified was either non-functional or lost its effectiveness in the title-based searches on DBLP and Google Scholar. Therefore, a second keyword is created to represent our search scope in general. Consequently, we have concluded that our scope can be detected in the metadata. Finally, the search process was done with the keywords in Table 1 on the November of 2021.

After defining the keywords and libraries a pilot search was done by the first three authors to make sure the search process that would be applied is standard across the research. Based on the scope and context of our study, for the selection of papers, the following propositions of inclusion criteria (IC) and exclusion criteria (EC) were specified and applied. The steps of the search process were conducted by the first three authors individually by evaluating the detailed inclusion and exclusion criteria to the papers.

- *IC1: Comparing PM tools within any aspects*
- *EC1: Papers not available in English.*
- *EC2: Papers published in non-peer-reviewed sources such as thesis, web pages, and books.*
- *EC3: Papers not accessible by the authors*
- *EC4: Papers not providing any content to compare PM tools*
- *EC5: Papers comparing PM algorithms, not tools*

Among these exclusion criteria above, only EC1 was applied by embodying it in special settings in the search parameters proposed by Web of Science and Google Scholar. For the rest of them, all these three exclusion criteria were applied manually by the researchers.

During application inclusion/exclusion criteria, the papers were examined through their titles and, where necessary, abstracts in order to identify whether they are in our scope. If the abstracts were not sufficient to decide to include or exclude the papers, then, scanning through the full texts of the papers was done to identify potentially relevant ones. After three authors identified their selected papers, the paper lists from these three authors were then compared to each other. Once there was a disagreement, the authors discussed the issues until they reached a consensus. In this step, exclusions from and inclusions into the list were made, resulting in the final agreed-upon list. The whole search process was coordinated by the third author and reviewed by the fourth author to propose improvements if needed.

In the process, a total number of 318 peer-reviewed works were returned from the search results as seen in Table 1. This initial list included duplicate records due to the fact that databases we covered perform meta-data indexing of publishing databases we included directly. After removing the duplicate records, the list included 194 distinct records. Out of these 194 papers, 55 papers were investigated only through their titles, 111 of them through their titles, and abstracts and 28 of them through their titles, abstracts, and full texts. Out of these 194, even though they are within the scope of our study, 5 studies were ignored as they are not peer-reviewed thesis coming from Google Scholar, in relevant EC2. Any exclusion was not applied regarding EC3; because all papers' abstract and selected ones' full text contents were accessible by the authors. We applied EC1 (papers not available in English) either by filtering via the library relevant features allowing eliminating non-English study forehand or otherwise via manual investigations by the authors. EC3 and EC4 are more about the content details of the papers. They are applied during the meta-data or the full text data investigation stages. During the content-based selection, 171 studies do not provide any kind of tools comparison. Seven studies include a comparison for PM algorithms not for tools. One study compares models but not tools. One study provides a comparison method only. Consequently, nine papers that compare PM tools within the scope of our study were identified.

For the nine relevant papers, they were allocated randomly to the first two researchers. The first and second researchers run separate sessions in order to extract the data that serves to answer the research questions by applying detailed and thorough examinations of the relevant studies.

Table 1. Search Process Results

Search Library	Place	Search String	#Initially Retrieved
ACM DL	Metadata	"Process mining" AND Tools AND (Comparative OR Comparing OR Comparison OR Compare OR benchmark)	7
IEEE			46
Science Direct			18
Scopus			104
*Web of Science	Topic		96
**Google Scholar	Title	"Process mining" AND Tools	23
***DBLP	Title		24
Total			318

* Web of Science does not provide searching in metadata except specific to the topic
** Google Scholar does not provide searching in metadata except specific to the title
*** Number of the results from DBLP allows to make a manual search with the broader string as given

4.3. *Quality Assessment*

The entire process relies on a sophisticated search procedure that calls for explicit criteria to validate the quality of the selected candidate papers by ensuring each candidate paper is of adequate standard. Accordingly, a custom quality-assessment-criteria-list along with their weight for the final score and descriptions were established as shown in Table 2. Each paper has been then assessed against this given set of questions by the assigned authors. A manual inspection was done though the full text investigation carried out to identify each selected paper's quality assessment score. To assign the weight of each creation, we set a score- weight between 0-5 based on the three scales; Fully Satisfactory, Partially Satisfactory and None. As seen in the Table 2 the score of Fully Satisfactory may not equal for each creation; when it is more important in terms of quality, the score- weight gets higher for the particular creation. Accordingly, the evaluations of the papers have been made based on the predefined three scales (Fully Satisfactory, Partially Satisfactory and None) to set their scores. For instance, if a paper gets the full scores, it can reach to 20 (4+5+3+5+3) that is then divided by 5 (the number of criteria) yielding the score of 4 at maximum.

Table 2. Criteria for Quality Assessment

Criteria	Statements	Score of Fully Satisfactory (out of 5)	Score of Partially Satisfactory (out of 5)	Score of None (out of 5)	Descriptions
QA1	Does the paper provide valid reasons to cover the compared tools?	4	2	0	It is clearly stated why the relevant tools are selected to compare
QA2	Does the paper provide a sound method for the tools' evaluations?	5	2	0	There are questions about the clarity and robustness of the method
QA3	Are the evaluation criteria clearly stated with their reasons?	3	1	0	The reasons why those criteria were chosen are stated
QA4	Are the evaluation criteria valuable?	5	2	0	Criteria are subjects that give valuable insights and/or require relatively high effort to get results through them
QA5	Does the paper provide clear results for the tools' evaluations?	3	1	0	Results are partially confusing/ Results are mostly confusing

After applying the determined quality criteria, the quality scores of each study are as in the Table 3. Due to the relatively low number of relevant studies, we did not want to set a threshold value to reduce the number of studies any further. Rather than omitting any relevant studies, the quality criterion remained just as an information that did not lead us to any action. However, the studies assigned the lowest quality score have a minor part of the whole.

Table 3. Quality Scores of Each Study

Study	QA1	QA2	QA3	QA4	QA5	Average Score
[3]	Partially	Partially	Partially	Fully	Fully	2,6
[4]	Fully	Fully	Fully	Partially	Partially	3
[5]	Partially	Partially	Partially	Partially	Partially	1,6
[11]	Fully	Fully	Fully	Fully	Fully	4
[22]	Partially	Partially	Partially	Partially	Partially	1,6
[23]	Fully	Fully	Fully	Partially	Partially	3
[24]	Fully	Fully	Fully	Partially	Partially	3
[25]	Fully	Fully	Fully	Fully	Fully	4
[26]	Fully	Fully	Partially	Fully	Fully	3,6

4.4. Data Collection

Based on the research questions, we identified the relevant data to extract from each study. The data extracted from each study were paper title, author(s), author country, publication year, venue type, strengths and weaknesses of PM tools, comparison method, other findings such as sector adopting PM tools, comparison criteria and compared tools.

Two iterations were made to check and investigate what can be extracted and, accordingly, whether a possible update on the research questions was needed. Two points were taken into consideration in the first iteration; is it possible to find the answers to the research questions. Secondly, can any other relevant research questions be added? Although it was realized after the first iteration that it was not possible to find answers to all of our research questions in each paper (for example, sector information is rarely included), despite the incomplete information it was decided that satisfactory information for the research questions can be reached. Therefore, the research questions were preserved as they are. The data to extract from each study were identified as following. The third author coordinated the data extraction process which involved the first two authors of this paper.

4.5. Potential Threats to Validity

We systematically identified and addressed potential threats to four types of validity of our research based on the guidelines of systematic literature review and mapping studies [27, 28] and below, we describe the steps that we took to minimize or mitigate these threats as adapted from [28].

Internal validity: Limitation of search terms and search engines can lead to an incomplete set of primary sources. In order to mitigate the risk of finding irrelevant studies, a search was undertaken using defined keywords, followed by a manual search among the references in the initial pool and the ResearchGate pages of most contributing researchers in the field of study. To minimize threats that may result from search engines, we not only included comprehensive academic databases, such as Google Scholar but also searched special active venues and webpages related to PM. We recorded in an Excel sheet each paper found with its source. In cases where several sources returned the same paper, all sources were noted. Therefore, we believe that an adequate and inclusive basis was established for this study and if there was any missing publication, the rate would be negligible.

Construct validity: In this study, threats related to this type of validity concerned the suitability of RQs. The research questions were specifically designed for the defined goal and different aspects of PM tools. The questions were systematically answered and finalized through several iterative improvement processes.

Conclusion validity: In order to ensure the reliability of our treatments, the entire pool of primary sources was analysed and the data were reviewed, extracted, and synthesized by the first three authors in iterations according to a research protocol, and the whole process and all selected outputs were reviewed by the third author. In addition, following the guidelines of a systematic literature review approach and procedure ensured replicability of this study and that the results would not significantly deviate from those of other similar studies.

External validity: Defining search terms in the source selection approach resulted in obtaining only primary sources written in the English language. However, the main issue concerns whether the selected works represent all types of literature in the area of study, and we consider that the relevant studies collected in the study pool contained sufficient information to represent the entire related literature.

5. Results

In this section, we present and discuss the results of the SLR study in relation to research questions. Regarding the compared PM tools Section 5.1 delivers total number of comparisons for the tools. Section 5.2 provides both methods and criteria used for comparison in the identified studies. Related to RQ3, Section 5.3 addresses strengths and weaknesses of compared PM tools from the papers. Lastly, in relation to trends and demographics of the papers, Section 5.4 gives information about author(s)'country, year of publication, venue of publication and current citation numbers in Google Scholar.

5.1. RQ1: Compared PM Tools

Through the SLR results, which tools are compared in studies and how often they are compared are depicted in Table 4. It is observed that the compared tools in the studies provide a variety but most of the studies use the same set of tools such as ProM [29], Disco [30], and Celonis [31] which are the most popular commercially available products in the market.

Table 4. PM tools compared in the reviewed studies

PM Tools	Number of Comparison
ProM	7
Disco	7
Celonis	4
ARIS Process Performance Manager (PPM)	3
Apromore	2
bupaR	1
PMLAB	1
QPR	1
Signavio	1
Fujitsu Automated Process Discovery Service (APDS)	1
Futura Reflect	1
Fluxicon	1
Iontas Focus Suite	1
Comprehend	1
BPM one	1
My-Invenio	1
ProcessAnalyzer	1
ABBYY	1
BusinessOptix	1
EverFlow	1
LANA Process Mining	1
Logpickr Process Explorer	1

5.2. RQ2: Comparison Methods or Criteria

Omori et al. [25] used a method which is relying on the drift detection ability of the tools to compare them. Drift detection methods provide a set of parameters that is a variation of those parameters results in different outputs of drift detection result. All tools are compared by testing the drift detection abilities with specific parameters that affect the drift detection capabilities of the tools. Each parameter is adjusted repeatedly for the different tests during the method.

Leemans et al. [11] used a comparison method which is considering the four main headings such as representation and process discovery techniques, enrichment, zoomability, and finally evaluation and deviations. The tools that are planned to be compared in this article are Fluxicon Disco (FD), Celonis Discovery (CD), Perceptive Process Mining (PPM), and Fuzzy Miner (FM), the chain (IMi-C) which is the collection of the set of plugins such as Inductive Miner - infrequent (IMi), PNetReplayer and Project Manifest to Model for conformance, and another chain (ILP-C) consisting of ILP miner, PNetReplayer and Project Manifest to Model for conformance. Chains of plugins are allowed to be compared in these articles in order for the comparison to be fair. The comparison of these tools is finalized by summarizing the feature comparison of the four main headings and then a case study is applied to see the responses of the tools. Two real-life logs are used in this case study, these are a log of financial institution (BPIC12 [32]) and a log from a building permit approval process of a Dutch municipality (WABO1BB [33]).

In [3], the PM used in the processes called ProM, Disco, Celonis and My-Invenio were examined and their performances were compared according to their usage characteristics. According to the results obtained, the usefulness, performance and reporting features of the software used in a process analysis have been revealed. In [5], Comparative analysis of PM tools is executed. It includes results of PM instruments comparing. Systems are evaluated by scale from 0 to 10, where 10 is the maximum mark. In [23], potential criteria from previous studies were identified with a literature review and the selected software is experimentally tested.

Table 5. Criteria Used to Compare the Tools

Criteria/Paper	[5]	[3]	[4]	[11]	[25]	[26]	[23]	[24]	[22]
Process model		x				x			
License		x	x					x	
Input level				x					
Importing & Exporting		x		x				x	x
Filtering		x	x	x				x	
Algorithm & Techniques		x	x	x		x	x	x	
Conformance checking							x		
Supported platform	x								
Process model notations								x	
Process mining problem						x			
Additional Features						x			
Local tool				x					
Executable semantics				x					
Guaranteed soundness				x					
Guaranteed perfect fitness				x					
Best-possible precision				x					
Representational bias Q parallelism				x					
Representational bias > ILP-C				x					
Representational bias ¥ process trees				x					
Avoid parallelism-clutter				x					
Frequency enrichment				x					
Path frequency filter				x					
Animation				x					
Immediate parameter feedback				x					
Long-distance dependency filter without model replacement				x					
Detection method					x				
Windowing					x				
Feature selection					x				
Sensitivity					x				
Noise					x				
Drift characterization					x				
Stream type					x				
Process visualization	x								
Performance reporting	x								
System integration									
System functionality									
Product version									x
Output type									x
Supported features									x
Importance of design priorities									x
Data management							x		
Operational support							x		
Views, monitoring and reporting							x		
Security & compliance							x		
Process visualization		x							
Social network mining		x						x	
Browser-based		x							

Turner et al. [26] follow a methodology that includes three phases for comparative analysis of business PM tools. The first phase of the methodology is focusing on the identification of the commercially available PM tools which are capable of performing PM and in addition to this it is important for tools to be located in major search engines with an academic citation. The result of this phase has provided the identification of five tools as Futura Reflect, Fluxicon, ARIS

Process Performance Manager, BPM One, and Fujitsu Automated Process Discovery Service (APDS). The second phase of the comparative analysis is held by the authors by identifying the features and capabilities of the PM tools. The important and relevant information about the business PM tools that are identified at the first phase of the comparative analysis is extracted from the website of the PM tools, academic or technical papers. The collection of information is summarized by the authors according to the common abilities and features of the identified tools in order to determine the comparison criteria. At this stage of the comparative analysis, the collection of criteria is listed under three main sections as “algorithm”, “process mining problem” and “type of process mining”. In the third phase of the methodology of the comparative analysis of the business PM tools, the determination of the comparison criteria is reviewed and finalized by the experts with a minimum of five years of experience in the sector. The determination of the comparison criteria by the group of experts creates quality and a better understanding of the requirements from the industry.

In [4], the paper introduces a comparative analysis methodology with two phases that can be used for the comparative analysis of any number of PM software tools and describes Analytic Hierarchy Process (AHP), which can be used in order to help users decide which software tool best suits their needs. In [24], the methodology is applied in a case study that is based on the comparison of two most prominent PM tools, against their technical and performance features. The comparison of these tools is presented, resulting in a creation of a solution that combines the strengths of both tools.

Criteria that are used to compare the tools were gathered from each paper and presented in Table 5. The criteria column is used to indicate if there are any common criteria category among the comparison criteria. As in the “input” category, there are common categories covered in the same study, as well as multiple studies using different criteria under the “algorithm & techniques”, “filtering”, “importing & exporting”, “license” and "process model” categories. Although few in number, “input type”, “conformance checking”, and “social network mining” criterion items are used by multiple studies.

5.3. RQ3: Strengths and Weaknesses of Compared PM Tools

ProM has a user interface problem which is not easy for beginners [3]. Although ProM open system supports extending and adding system functionality for users, conduct research and solve actual Data Mining problems [5]. ProM aims largely at the academic and research community. It offers less input type possibilities than Disco, although both tools do have a converter to extensible event stream (XES) event log format that is a standard event log format for PM [24]. Some of its features are conformance checking, social network mining [2, 11], process discovery, process analysis, simulation, filtering, etc. [4].

Disco has an easier to use user interface and anybody can easily understand how the PM is evaluated [3]. Disco is more efficient to use by small and medium businesses. Such a system is convenient, easy to use and oriented on clients [5]. The program really a great academic tool set, which makes it very easy for researchers to develop algorithms and for business professionals, who do not need to know anything about how these algorithms work [22]. Disco offers only one algorithm, Disco miner [30], which is an improvement of existing fuzzy miner, and therefore only one model notation, fuzzy model [24]. Some of its features are process discovery, event log filtering using various parameters, project management, animation, detailed statistics, etc. [4]. Performance analysis is possible in both ProM and Disco tools, although Disco shows information about throughput times, waiting times and bottlenecks along with the discovered fuzzy model and ProM requires application of performance plug-in on a model in a petri net notation [24].

Celonis is a commercial tool. On the other hand, Celonis has its unique design and supports a custom designer. Celonis PI is a web-based edition of Celonis software that uses advanced artificial intelligence and machine learning capabilities [3]. Some of its features are: Real-time surveillance of business transactions, process analysis, automated integration of source data, process reporting, filtering [35], browser-based, real-time optimization, etc. [4].

The created maps by Celonis Discovery (CD) and Fluxicon Disco (FD) and some of the chain of plugins of ProM sometimes can be categorized as difficult-to-interpret maps. In addition, it is possible to say that some of the tools might fail to produce readable maps at all. In such cases, it is suggested that fine-tuning parameters of the tools might improve the readability of the maps that are created by the tools especially in Celonis Discovery and Perceptive Process Mining [11]. The commercial tools CD, FD, and PM are able to provide an easy-to-use interface to users with features such as parameter feedback, log animation, and filtering options. It is observed that the process maps that are created by the commercial tools which are stated above either do not have parallelism and executable semantics thus deviations cannot be computed properly [9]. ProM and its plugins are able to create a process map with executable semantics and thus deviations can be computed and analyzed by using the replay feature and alignment techniques of the tool. One of the disadvantages of ProM in this process is that some of the features that are important for process exploration are missing. Another disadvantage of ProM is, unlike the commercial tools, it is able to create a successful process map with a chain of plugins and this makes the process non-interactive and slow.

Aris Process Performance Manager (PPM) provides ease such as quantitative measurement of objectives and visualization of process instances [26]. It also provides an aggregate process view compilation which can be resulted in a process map that is created by using Event-Driven Process Chain (EPC) notation. Aris PPM supports the Key Performance Indicator (KPI) information that can be annotated to the process instances. The interactive analysis feature of the tool allows users to discover performance bottlenecks in the process.

Fluxicon Disco is able to discover processes and social networks. It also provides detailed descriptions of process executions and identification of bottlenecks within a process [26]. The tool is able to visualize the control flow of processes and utilize process documentation in which users can see the process goals and the actual process.

The capabilities of Futura Reflect can be listed as process discovery, process animation, social network discovery, and performance analysis capabilities [26]. Comprehend provides information capture, process-centric business intelligence, process identification, attribute-based filtering, and a process deviation discovery. It allows users to gain insights about the processes and explore the deviations in processes easily. Iontas Focus Suite provides facilities such as automatic discovery and visualization of business processes, identification of inefficient process flows and best practices, access to individual process details, and suggestions for process improvements.

BPM One is able to handle process discovery. The process discovery of the BPM One is completed after several iterations. After each iteration, the previous iteration is improved and as a result of all iterations, the final process model is concluded. In addition, a filter for incomplete or exceptional process instances can be applied [26].

Fujitsu Automated Process Discovery Service (APDS) is able to automatically discover the processes and visualize the process model with if there are any process bottlenecks. It highlights inefficiencies in the processes and provides a comparison result of the current process model with the pre-existing templates [26]. APDS also provides process comparison utility which is an analytical tool that helps to improve processes.

Specifically, ProDrift, ProM, CDESF, and TPCDD are able to detect process drifts. The drift detection abilities of these tools are mostly depending on the knowledge of the user about the subject. The decision of selecting which tool to use for detecting process drift is heavily dependent on the solution’s output and the level of knowledge required for managing it [25]. According to [26], “ProDrift and ProM are better choices for users who want an easy to use albeit not customizable tool, while CDESF and TPCDD are better choices if you have the know-how to be able to execute and customize it to your needs.”

5.4. RQ4 Trends and Demographics

All studies included in literature review are shared in Table 6 (ordered by Year) along with study reference, author(s)’country, year of publication, venue type, venue name, and current citation numbers in Google Scholar. Regarding RQ4.1: Top Venues, we have found the number of published papers in each venue to identify the top venues by type. Of the 9 venues on this list, five of them were conference and four were journals. However, each value is identical, having only one paper at most. Related to RQ4.2 Top-Cited Publications, it is seen that the two prominent studies are a journal paper [26], and a conference paper [11]. However, as a note, it should be considered that these two studies were published in relatively earlier years. Regarding RQ4.3: Publication Count by Year, the distribution of published number of studies by year of publication is as shown in Fig 1.

Table 6. Trends and Demographics of Studies

Study	Author(s)' Country	Year	Venue Type	Venue	# Citation
[26]	United Kingdom	2012	Journal	Business Process Management Journal	98
[5]	Russia	2015	Journal	International Journal Information Models and Analyses	2
[11]	Netherlands	2015	Conference	International Conference on Business Process Management	68
[3]	Turkey	2018	Journal	Online Academic Journal of Information Technology	9
[22]	India	2018	Journal	International Journal of Innovative Research in Applied Sciences and Engineering	0
[4]	Greece	2019	Conference	International Conference on Knowledge Science, Engineering and Management	1
[24]	Serbia	2019	Conference	International Symposium on Intelligent Systems and Informatics	8
[25]	Brazil, Italy	2019	Conference	Brazilian Symposium on Information Systems	2
[23]	Germany	2020	Conference	The IEEE International Conference on Process Mining (ICPM)	2

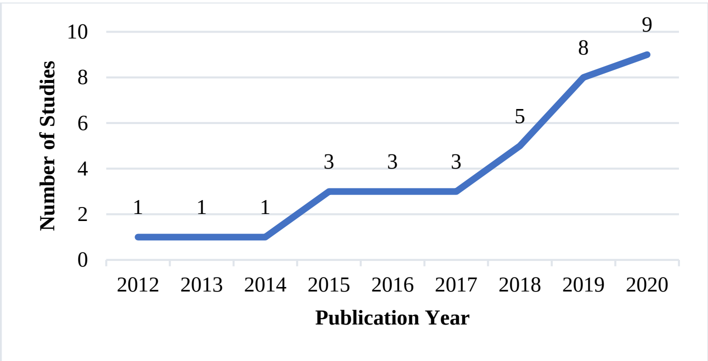

Fig.1. Accumulative Number of Published Studies by Year

6. Discussion

A review is a good approach to have a clear visibility about a topic and to give an overall idea about a subject in details [35]. Our SLR may provide visibility and insights about the subject we focus on through the identified RQs. Related to RQ1 (compared PM tools), it is obvious that the most compared tools are ProM and Disco with seven mentions in the reviewed articles. The possible reason for this is because ProM supports open-source and no payment requirement for academic or commercial use and Disco is a commercially available tool that provides a useful user experience and insightful information. The popularity of ProM can be realized when the search string “ProM process mining” is checked at the Google Scholar database yielding 67,600 results which shows the importance and the popularity of this tool in the community [26]. In our basic research in Google Scholar with “process mining” + tool name (such as “process mining” ProM or “process mining” Disco), we found a similar order between the tools; 5.390, 1780, 598, 270, 116 results for ProM, Disco, Celonis, Apromore and bupaR respectively.

When it comes to the comparison methods or criteria (regarding RQ2), we have seen that there are many criteria used in the comparison of the tools. Interestingly, the studies do not pose a common ground for the criteria sets. Only five items are shared by the multiple studies. They are License, Conformance checking, Input type, Supported platform and social network mining. Most of the criteria that are used to compare the PM tools in the articles reviewed show a variety from article to article. Although there are certain common criteria such as process discovery, conformance checking, and enhancement abilities of the tools, most of the criteria are selected after careful consideration of the results of the different methodologies by the authors in the articles. This shows that there is no common way of comparing the tools and the comparison process needs different parameters such as sector and user experience. It can be seen that the commercial and academic tools are compared by using different sets of criteria because the need for the tools are depending on the situation where the PM is going to be applied and how the results are going to be analysed. It is also seen that although most of the articles that are reviewed follow a methodology to eliminate a problem by focusing on what are the correlations between the selected criteria and the effects of these criteria on user experience, some of the articles did not follow such a methodology. The articles that did not follow such methodology are using very basic criteria to compare the tools and those criteria do not provide any relation with user experience and insightful information for the tools.

While articles with high scores provided more understandable information in terms of the methodology and evaluation criteria that they presented, it was difficult to understand this in articles with low scores. In comparison studies, we have seen that clearly determining the criteria and giving the methodology has positive benefits in understanding the article clearly.

It is also observed that some of the articles only focused on a specific capability of the PM tools such as in terms of their drift detection ability and this approach shapes the criteria that are selected to evaluate the PM tools. The evaluation criteria in these articles showed us that the expectation from the PM tools might differ in terms of their ability to do more specific jobs other than the basic PM steps. Although this approach on the evaluation of the PM tools might provide significant information based on the specific ability test for the PM application area, it was seen that most of the articles did not follow such methodology.

Relating to RQ3, as outputs of the evaluations, the strengths and weaknesses of the compared PM tools can be observed. It is observed that the articles did not provide the strengths and weaknesses of the PM tools as a result of their evaluation, instead these are inferred from their evaluations. This is because most of the articles used the evaluation criteria as binary decisions to indicate whether PM tools can perform a specific task or not. The additional information about the application of the PM techniques i.e., the area of the tools that are going to be used can be more useful information with an additional metric that represents the performance of the tool during the application. Such metrics can be created based on the user experience case by case with the help of surveys. When a comparison of PM tools is made, the lack of PM application parameters such as sector, time, data size etc. might have a significant impact on determining which tool to use and thus determining strengths and weaknesses of the PM tools.

Regarding the trends and demographics (RQ4), most of the studies were published in the conferences and the rest of them were published in the journals. In this distribution, the situation in favour of the conference may be because of that such innovative topics first try to find a place in the conferences rather than journals. However, only ICPM (International Conference on Process Mining) was observed as a dedicated conference on process mining. All the others, although not dedicated, includes the relevant studies. Although there appears to be an increase in the number of studies in recent years, this increase is not evident. Considering our survey does not cover the full year of 2020, it is not possible to indicate that there has been an upward trend in recent years. In general, the relatively small number of articles and the fact that academic publications lag behind the industry momentum is a possible situation in such areas where the practice is more dominant than the academic side. Not surprisingly, the country distribution of the authors is largely in the European continent, where can be considered the origin of PM and it is most widespread.

Another important issue is that the area of the tools that are going to be used has an important effect on determining which tool to use. Therefore, highlighting the sector and area in the articles provide ease for the audience of these articles to determine which tool to use in a specific situation. Some of the articles that are reviewed in this study ignore this fact and just present a general comparison of tools. It is important to highlight the sector and area of application of the tools. For example, some tools are able to provide a simulation feature that allows users to interact with the processes one by one. This kind of feature can help users to analyse the processes in a more detailed way with the help of outputs that are created by PM applications. Therefore, the sector and area can affect the comparison of the tools. While PM tools can help organizations analyse processes in almost every sector, it is currently quite popular in the health sector.

According to Figure 1, the number of comparison studies increased in the last eight years. It can be interpreted as PM practitioners have a difficulty determining the right PM tool for their business. Because of the increasing number of PM tools and the need for interpretation of the event logs, practitioners should determine the right PM tool with respect to time and efficiency criteria. The difficulty that practitioners have during the selection of the right PM tool can be proven by the increase in the comparative studies of PM tools. As it is stated above, there are many PM tools with a range of features, algorithms, and visually enhanced presentations. Most of the papers that are evaluated do not provide a comparison methodology. The criteria that are used in these papers do not contain consensus and almost all the papers provide a different set of criteria to compare a specific set of PM tools. This causes a conflict between comparison studies and does not provide ease for the decision maker to select the right tool.

7. Conclusion, Limitation and Future Work

Used by varying industries, PM tools play an important role in business process effectiveness for organizations. Therefore, it is critical to consider PM tools' abilities and determine the right tool for an enterprise, which calls for a comprehensive comparison of the tools in the market. Having a lack of review studies in this regard makes challenging for the evaluators to come up with a decision in this selection. Considering the current gap in the academic literature, we conducted an SLR to review and analyze the studies that contain a comparison of the PM tools. Our study exhibits valuable and easy-to-consume results both for practitioners and researchers. Specifically speaking, in order to fully understand the effects of tools in extracting the valuable information from event data, the results of this SLR can be used. The most commonly used tools in comparison articles can be listed as Disco, ProM and Celonis. Typically, PM tools are compared according to the three types of information in the articles; the abilities of process discovery and the algorithms that they use to do and the ability of conformance checking. By process discovery, the tools produce process maps, based on event logs without any assumptions about the process of the organization. With conformance checking, it allows comparison of event logs with existing process models in organizations and it brings up the potential points of flow for optimization thus enhancement on the process model for better process models. Since the previous articles were examined, general features of the related applications are mentioned in the articles, considering that the deficiencies mentioned in the articles can be eliminated in the prospective versions. Although there are common criteria used in some of the articles that are used in this SLR, there are still avenues that can be study topics for further research.

With the increase in the variety and volume of data accumulated on various platforms in the enterprises, it has been seen that machine learning techniques have begun to be used in the processing of these data and obtaining meaningful information.

Most of the articles about the comparison of the existing commercial or academic PM tools are focused on the abilities of PM tools and the ways of dealing with some common problems such as bottlenecks, noise, etc. Although there is an example of the way of comparing existing PM tools for academic use by covering it with a case study which simulates the environment that the tools are going to be used, as the limitations of current research, there are less examples of articles about the comparison of the existing PM tools for commercial use by focusing on the user experience. It is proposed that articles that are going to be focusing on the user experience rather than the general capabilities of the tools might be providing more insightful information about the tools. The user experience that the tools provide for the users must be meaningful and relevant to the context of the data. Therefore, it is important for tools not only to be able to handle generic requirements of the PM but also to provide a useful experience of these requirements for their users.

The procedures used in our study have limitations in several ways:

- More likely, we may have missed some relevant studies as we did not include all possible libraries. In particular, we have missed the studies published in not-peer-reviewed sources.
- Due to the relatively large number of studies, we did not separately record information about how many studies were eliminated based on each exclusion criterion. In addition, we did not keep track of the duplicate records.
- A single researcher extracted the data from the studies, although the studies included were checked by other researchers.
- With respect to the quality of the selected studies, due to the relatively low number of relevant studies, we did not want to set a threshold value to reduce the number of studies any further. Rather than omitting any relevant studies, the quality criterion remained just as an information that did not lead us to any action. Therefore, we have likely erred on including studies that were not very systematic. However, the studies assigned the lowest quality score have a minor part of the whole.
- The quality assessment criteria are somewhat subjective and not a ready-made invented measure.

We have not seen a study among the existing works that makes a qualitative comparison. Since the current studies are far from the real experiences in the field, we are planning a study that evaluates the experiences of the most used open licensed and/or platform tools from the end-user and the developer perspectives, both qualitatively and quantitatively. In this sense, we aim to comprehensively compare the bupaR (Process Mining in R) and PM4Py (Process Mining for Python) tools since they provide an open-source environment providing flexibility to the developers.

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Authors' Profiles

Cuma Ali Kesici recently undergraduate industrial engineering program from the Ihsan Dogramaci Bilkent University. During his education in the university, he had opportunity to study operations research, production systems design-synthesis and data analysis. His recent internship experience in Kuveyt Türk Participation Bank and curiosity to discover and understand the potential of event logs led him to participate in Process Mining studies and projects. As a process mining intern, he contributed to the quality control and improvement project about comparing open-source process mining packages on R and Python programming languages.

Necmettin Ozkan has first-hand professional experience in IT quality, process and performance management and Agile Software Development. Among the frameworks, he closely works with ITIL, COBIT, Scrum, and Kanban. He is passionate about contributing to the body of knowledge by sharing through public speaking, academic publications, and as a reviewer for international journals and conferences. He is working toward his Ph.D. degree at Gebze Technical University and as the IT Quality Team Leader at Kuveyt Turk Participation Bank. His research interests include agile software development and agility. Contact him at necmettin.ozkan@kuveytturk.com.tr.

Sedat Taşkesenlioglu started his career as a technical internal auditor in 2007. He has audited many domestic and international projects in the field of Telecom, Textile, Construction, Energy, and IT. He has been working as an IT Quality Management Engineer in KT Bank for eight years. He received his M.Sc. from Management Information Systems, Sakarya University. He has participated in projects about Process Mining and predictive ML models based on process logs analyzing IT processes in R and Python. His research interests include Process Mining, Data Science, and Process Improvement.

Tugba Gurgen Erdogan has been working as a researcher and practitioner in the area of software engineering and process mining for ten years. She received her Ph.D. degree from the Department of Computer Engineering, Hacettepe University, in 2018, where she received her B.Sc. and M.Sc. degrees and works as a lecturer in the same department. Her research interests include software process improvement, empirical software engineering, software development methodologies, process mining in healthcare, data privacy, and machine learning. During her academic affiliations and research collaborations, she has supervised many graduate students' studies in their M.Sc. and included and led to academic national and international projects, outputs of which have been published in various journals and conference proceedings.

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