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# A Systematic Review on Recommender Systems in Process Mining

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Abstract Considering processes of a business in a recommender system is highly advantageous. Although most studies in the business process analysis domain are of descriptive and predictive nature, the feasibility of constructing a process-aware recommender system is assessed in a few works. One reason can be the lack of knowledge on process mining potential for recommendation problems. Therefore, this paper aims to identify and analyze the published studies on process-aware recommender system techniques in business process management and process mining domain. A systematic review was conducted on 33 academic articles published between 2008 and 2020 according to several aspects. In this regard, we provide a state-of-the-art review with critical details and researchers with a better perception of which path to pursue in this field. Moreover, based on a knowledge base and holistic perspective, we discuss some research gaps and open challenges in this field.

Keywords Process-Aware Recommender Systems · Process Mining, Prescriptive Business Process Monitoring · Operational Support · Activity/Resource Recommendation · Literature Review

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#### 1 Introduction

Most of the information systems maintain significant volumes of records of process execution events, like executing a task for a particular process instance. Process Mining (PM) is a relatively new research field [2], which intends to extract insights from the event data stored and maintained in the databases and information systems, known as event logs. PM techniques' primary objective is to apply the event data in extracting process-related information, like constructing a business process model from the observed behavior in an automated sense. An event log is a collection of events extracted in the context of a process that indicates which activity has happened at a specific time [68]. Moreover, a Process-Aware Information System <sup>1</sup> is a software system able to produce, maintain and manage the event logs (e.g., ERP<sup>2</sup> systems, CRM <sup>3</sup> systems, and HISs<sup>4</sup> [21].

Most of the current business process analytic studies have mainly applied PM as a stand-alone application in an offline mode to discover and evaluate process models. There exist emerging efforts in predictive analytics, where typical methods mainly consist of data mining, machine learning-based prediction, and simulation [40]. These approaches share the following common drawbacks.

- They do not suggest nor prescribe potential improvement actions to decrease the probability of inappropriate outcomes but promote the user's subjective judgment and analytical skills to induct enhancement actions.
- 2) The optimization procedure is executed after process complication, not during [1].
- 3) These techniques assume that process participants can take the most proper action manually to assure the optimal accuracy for their scenario. However, in practice, the optimal accuracy depends on different factors like different costs of process execution.

Though PM has the potential to offer many advantages to recommender systems, few studies exist where the feasibility of constructing a Process-Aware Recommender System (PARS) is assessed. Possibly operational support is the most comprehensive process mining task, where additional profits can be gained by applying the PARSs. Next to supporting the decision-making process by filling the gap between pure analysis and operational support, PARSs can be contributive in decision rules analysis adopted in different instances. For instance, offering suggestions about possible next activities or resources during the process execution, reducing the overall running time, costs, and the possible risks involved in specific situations to optimize the KPIs<sup>5</sup> are some

<sup>&</sup>lt;sup>1</sup> PAIS

 $<sup>^2</sup>$  Enterprise Resource Planning

<sup>&</sup>lt;sup>3</sup> Customer Relationship Management

<sup>&</sup>lt;sup>4</sup> Hospital Information Systems

<sup>&</sup>lt;sup>5</sup> Key Performance Indicators

possible applications for PARSs. In general, PARSs can bring the most sizable intelligence and added value to businesses. In this context, not enough attention is directed to providing recommendations [48].

There are 28 review articles written in the PM: some have covered PM as a whole [47, 69], some have assessed the more detailed components like algorithms comparison [46, 90, 17] or a specific domain, e.g., health care [23, 28, 25, 65, 89], supply chain and industry [16, 33, 78] and education [12, 26]. There exist many review articles on process discovery [64, 10], conformance checking [22, 50], and predictive analytics [48, 63, 76, 45, 24, 81] in PM. As to prescriptive analytics in PM, the authors in [38] have assessed the process modeling recommender systems. The recommendation from the human resource point of view is evaluated by the authors in [9], where 90 relevant articles on the topic of human resource allocation and recommendation applied in BPM<sup>6</sup> and PM are reviewed, with no concern in recommending the next activity. A literature review is conducted by [40] on prescriptive PM, where merely the proposals in their implementation sense are assessed. They classified both the predictive and prescriptive methods in machine learning, statistical analysis, and probabilistic models.

As to the researchers here, a study is required to identify and classify the available studies regarding recommendation methods in PM in different contexts regarding the outline directions and provide researchers with a better understanding in their search in pursuing this concept. Consequently, the researchers in this field will have a holistic perspective on what has been done and the existing open challenges and future concerns. Therefore, we aim to assess the manner of recommendation techniques application in PM.

The rest of this article is structured as follows. Sec. 2 presents preliminary concepts. Then, the research methodology is expressed in Sec. 3. Afterward, the research findings and results are provided in Sec. 4, and the discussion is run in Sec. 5. Finally, the threats to validity are expressed in Sec. 6, and Sec. 7 concludes the article.

## 2 Preliminary concepts

This section explains some fundamental concepts used in this paper, i.e., process mining and prescriptive business process monitoring.

# 2.1 Process mining

Process mining is a research discipline that provides both data-oriented and business process-oriented analysis simultaneously. There are three main subfields in process mining, i.e., process discovery, conformance checking, and operational support [2].

<sup>&</sup>lt;sup>6</sup> Business Process Management

Process discovery aims to discover a process model that accurately describes the underlying process captured within the event data. An event log is given to the process discovery algorithm, and then it produces a descriptive process model as the output that captures the control-flow information among activities in different notations such as Petri net and  $\rm BPMN^7$ .

The second task is conformance checking that aims to assess to what degree a given process model and event data conform to one another. These approaches can exploit the deviations between discovered/reference process model and the corresponding event log and vice-versa to a better reflection of reality.

Finally, the operational support aims to improve or enhance process mining results, e.g., by reflecting bottleneck information directly onto a (given) process model. In this sub-filed of process mining, we try to enrich the process model, add emphasis, provide further information (e.g., time-stamps, KPIs, providing suggestions) to enhance the process model.

## 2.2 Prescriptive business process monitoring

The predictive business process monitoring consists of techniques applied in the upcoming status of current instances in PM [59] to improve the enabling proactive and corrective actions by providing on-time information. A predictive technique could predict the time necessary to execute a task in a running process instance, the next activity to be executed, or the end outcome. In the studies run in this context, suggesting or prescribing how the results can be applied in improving business processes are missing. Simultaneously, these two components should indicate how the process participants should intervene to decrease the potential of inappropriate results. To accomplish the process improvement objectives, the prediction results must be actualized in their concrete sense [4].

Prescriptive business process monitoring approaches measure predictions concerning their effect on the process performance to prevent inappropriate activities therein by warning or recommending. In this study, it is revealed that as to recommendation, there exist two major methods in PM:

1) Recommender systems during process modeling: support designers in design phases [39, 74, 95, 41]. Designing business process models are highly contributive in BPM. Simultaneously, in its manual sense, it is a time-consuming and an error-prone task. However, the required time may be reduced when the models' prototypes are generated through the modeling support techniques. The recommendation methods in business process modeling assist a designer in completing the process model editing. This assistance can provide autocompleting mechanisms to choose the next best nodes for the reference process fragments to complete the workflow. The model elements' names or attachments, the beginning and ending spots,

Business Process Management Notation

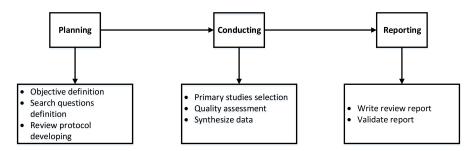


Fig. 1 Systematic review process [37]

and the abstraction level of the process model can be recommended as well. These approaches can reduce the structural error count during the process design, obtain a well-defined high-quality process model, and improve the performance of the modeling procedure.

2) Recommender systems during the process execution: continuously monitor process executions and predict how they are being evolved in determining the instances with a higher chance of not meeting the desired performance levels. In this way, they can provide automated recommendations of the possible best activities and resources to a running instance in order to optimize an objective function, performance, and efficiency or prevent an inappropriate outcome like case deviation, deadline, or risky execution.

The PARS, the focus of this study, was assessed by [71, 43] for the first time, where the process mining is applied to recommend users the possible next activity and resource, respectively. When a user requires a recommendation, first, its partial trace will be applied in the recommendation service. After that, it can be compared with the event log, and then some recommendations that would optimize the target function or match with a successfully executed behavior would be given.

# 3 Research method

Here, we explain the methodology of this review article that is based on the scientific guidelines specified in [37] (See Figure 1), and includes the research questions, the identification of queries, and the search engines. The steps for selecting the relevant studies are provided by applying inclusion/exclusion criteria.

#### 3.1 Background and objectives

According to [47, 23], descriptive analytics in PM has been the subject of more intense studies than other types of analytics (e.g., prescriptive). It could be a fundamental reason why the recommendation in PM has not reached the

Table 1 PICOC structure for directing the research question [36]

Criteria	Description
Population	Considering studies on how activity/resource recommendations during process execution are made in process mining Describe approaches (methods, strategies, techniques, and tools) ap-
Intervention	Describe approaches (methods, strategies, techniques, and tools) applied in PARSs
Comparison	N/A
Outcome	Describe the effectiveness of PARSs
Context	Describe the usage domain: primary studies in the BPM and PM disciplines

same level of maturity as other techniques [40]. To the best of the researchers' knowledge here, there is no extensive review study on this issue, and this is the first comprehensive review article focusing on the field of PARSs. Thus, a noble contribution in comprehending trends, challenges and filling the research gap herein. The objectives of this study are 1) to collect and characterize the studies where PM techniques are adopted to develop recommender systems, 2) refer to the existing PARSs' status, and 3) identify and classify the reviewed articles per most important aspects, like recommendation strategies, tools used, geographical areas, the application domain, where the data are acquired, and the problems are solved.

#### 3.2 Research questions

In line with this study's objectives, the research questions are defined as to focus on specific aspects of the overall evaluation. For this purpose, we used the proposed structure in [36] that is presented in Table 1. This structure includes Population, Intervention, Comparison, Outcome, and Context (PICOC) and is proposed to extract the related concepts applicable in systemic research questions. Because this article's composition is of systematic literature review type, the comparison of interventions is not applied.

In this paper, the research focuses are on the next activity/resource recommendations during process execution. The research questions mainly focus on discovering, identifying, and evaluating the approaches intended to apply recommendation techniques in the PM context. Here, we aim to answer the following research questions.

1) What are the trends and statistic of case studies where the PM techniques and algorithms were applied in the recommendation domain between 2008 and 2020?

This question aims to determine the rise and fall of the trend in published studies where PARSs are addressed in the given period. It is possible to identify the type of venues where the relevant studies are being published, contributing to the perception of relevant active journals and conferences in this field.

2) What are the common characteristics of the studies in the field of PARS?

Table 2 Generic Search Queries

'Recommender system' OR 'Decision support' OR 'Prescriptive analytics' OR 'Next recommendation' OR 'Next action recommendation' OR 'Next resource recommendation' AND 'Process mining'

Table 3 Published articles in journals, Conferences and PhD./Master thesis

Digital Library	Search Results
ACM	106
Google Scholar	1395
Emerald	111
IEEE Explore	71
Pubmed	56
Science Direct	461
Springer	53
Total	2253

For answering this question, the reviewed articles are classified according to different aspects, i.e., recommendation methodologies and approaches, applied tools, type of implementation, evaluation methods, geographical information, data type and application domains.

#### 3.3 Identification of search engines, keywords, and queries

In the third step of conducting this literature review, the search queries expressed in Table 2 are applied in the keywords, title, or abstract of published articles between 2008 and 2020. We investigated several popular digital libraries, i.e., ACM, Google Scholar, Emerald, IEEE Explore, Pubmed, Science Direct, and Springer Link. These search queries are the commonly-applied keywords in the relevant articles on PARSs.

The results obtained from each digital library are tabulated in Table 3. A total of 2253 primary studies are obtained through the *Identifying all relevant studies* phase in September 2020. After running the digital library search, all irrelevant content (1035 articles) and duplicates (72 articles) are excluded for the next phase. Thus, 1146 articles remained for further screening. This literature review is conducted subject to the inclusion and exclusion criteria, which are explained in the following subsection to assure unbiased selection.

## 3.4 Inclusion and exclusion criteria

In this phase, the inclusion criteria are applied to add a study to the analysis, and exclusion criteria are applied to exclude one from the analysis.

The inclusion criteria are as follows:

Table 4 Results obtained after applying each phase

Phase	Amount of papers		
Identifying all relevant studies	2253		
Removing duplicate or irrelevant studies	1146		
Applying the inclusion and exclusion criteria	105		
Screening of papers	52		
Full reading	33		

- IC-1: The recommendation method/algorithm/framework for the next activity/resource recommendation within the process mining domain.
- IC-2: Peer-reviewed articles in scientific journals, conferences, or workshops.
- IC-3: The article is written in English

The exclusion criteria are as follows:

- EC-1: The relation is only to one of the two areas considered in process mining or recommendation areas.
- EC-2: Concerning the process modeling recommender systems.
- EC-3: The focus is on resource allocation as to process performance improvement but not based on improving decision-making through process mining.
- EC-4: The article does not include a method/experiment/case study that is implemented and evaluated.

Based on these criteria, a total of 105 studies are considered in this study. Because this phase consists of studies with no contribution to the next activity/resource recommendation, the *screening of papers* phase is run to skim the metadata (i.e., title, abstract, and keywords sections) or those that do not correspond with IC1. After the screening phase, a total of 52 articles were extracted and remained for the *full reading of the articles* phase. After full reading, some articles were omitted according to EC-2 and EC-4, and reduced the count to a final set of 33 studies (13 journal papers, 19 conference papers, and four postgraduate and doctoral dissertations which were not on the scope of our review). The results obtained after applying each phase during the selection process are tabulated in Table 4.

# 4 Results

This section represents the undertaken data extraction phase results according to the protocol shown in the previous section. Figure 2 shows the publication venues of the selected research articles. Results show that the articles that belong to indexed journals make 35% of all. The relevant articles presented in conferences make up 51% of the total, and the International Conference on Business Process Management was make up for publishing seven articles of 19 conference articles. Moreover, 3% of articles belong to the technical report

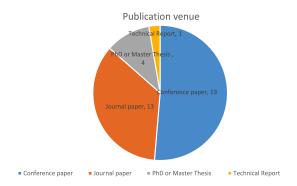


Fig. 2 Studies about PARS by venue

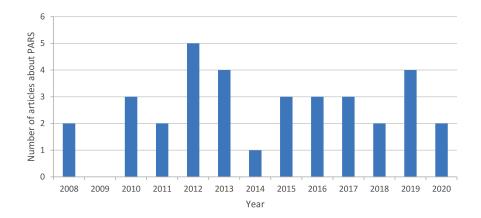


Fig. 3 Annual published articles about PARSs (2008-2020)

category, and 11% corresponds to postgraduate and doctoral theses that were not on our review's scope.

Concerning the distribution of studies about PARSs during the past 12 years, Figure 3, more than half of these studies are disseminated during the past five years, indicating a recent surge of interest in operational support tasks in PM. A complete list of these studies, including the authors' name, title, publication date, and method(s) is tabulated in Table 5.

# 4.1 Recommendation approaches and strategies

The available techniques for PARSs are classified according to *recommendation* approaches and *recommendation* strategies. In recommendation approaches,

 ${\bf Table~5}~~{\bf Classification~of~researches~regarding~PARSs}$ 

Authors	Publication	Recommendation Type	Process Perspectives	Contextua Infor- mation	al Application Domain and Data Type	Tools	Evaluation	Location
Schonenberg, et. al., (2008) [39]	International Conference on BPM	NAR, Metric-based	Control flow	-	-	ProM	Proposal of Solu- tion	the Nether- lands, Austria
Liu, et. al., (2008) [40]	Computers in Indus-	NRR- Pattern op- timizing	Control flow	-	Manufacturing enter- prises	WEKA	Evaluation Research	China Australia
Dorn, et. al., (2010) [47]	try International Conference on BPM	NAR, Metric-based	Control flow	Case level	web usage data	web- based pro- to-	Evaluation Research	Austria, Germany
van der Aalst, et. al., (2010) [44]	International Con- ference on Advanced Information Systems Engineering	NAR, Metric-based	Time	-	-	ProM	Validation Research	the Nether- lands
Motahari-Nezhad, et. al., (2011) [72]	International Conference on BPM	NAR/NRR, Pat- tern optimizing and Metric-based	Control flow and resource	Case level	Human resource	Eclips	Evaluation Research	USA
Haisjackl, et. al., (2010) [43]	International Conference on BPM	NAR, Metric-based	Control flow	-	-	ProM	Proposal of Solu- tion	Austria
Huang, et.al., (2011) [61]	Expert Systems with Applications	NRR, Pattern opti- mizing	Resource	-	healthcare	Weka	Validation Research	China
Chen, et.al., (2013)	Personal and ubiqui- tous computing	NAR, Pattern opti- mizing	Control flow	Case level	Web-based application	-	Validation Research	Japan
Schönig, et.al., (2012) [70]	International Conference on Collaborative Computing	NRR, Pattern opti- mizing	Data and Re- source	Case level	-	Weka	Validation Research	Germany
Petrusel, et.al., (2012) [51]	In International Con- ference on Business Information Systems	NAR, Metric-based	Control-flow, Data and Resource	-	-	ProM	Validation Research	Romania
Liu, et.al., (2012),	Knowledge-Based Systems	NRR, Pattern opti- mizing	Control flow and Resource	-	Manufacturing	Weka	Validation Research	China
[68] Barba, et.al., (2011) [45]	International Conference on BPM	NAR/ NRR, Met- ric based	Control-flow and Resource	-	-	ConDe	of Solu-	Austria
Nakatumba, et.al., (2012) [50]	BPM center report BPM-12-05	NAR, Pattern opti- mizing	Control-flow	-	-	ProM	Proposal of Solu- tion	the Nether- lands
Khodabandelou, et.al., (2013) [78]	International Con- ference on Research Challenges in Infor- mation Science	NAR	-	-	Human resource	Eclips, ProM	Validation Research	France
Triki, et.al., (2013) [59]	Workshops on En- abling Technologies: Infrastructure for Collaborative Enter- prises	NAR, Pattern optimizing	Control flow	-	-	Web- based pro- to- type	Proposal of Solu- tion	Tunisia, France
Obregon, et.al., (2013), [67]	In Asia-Pacific Con- ference on BPM	NRR, Metric-based and Pattern opti- mizing	Time and Re- source	-	Financial , Sales/ mar- keting	ProM	Validation Research	South Korea
Conforti, et.al., (2015) [66]	Decision Support Systems	NRR, Risk mini- mizing	Control- flow, Time, Resource	Case level	Insurance	YAWL, WEKA	Proposal of Solu- tion	Australia, the Nether- lands, Italy
Gröger, et.al.,	International Confer-	NAR, Pattern opti-	Control-flow	Process	Manufacturing	RapidN	Ii Werdidation	Germany
(2014) [48] Zhao, et.al., (2015) [71]	ence on BPM International Conference on Intelligent	NRR, Metric-based	and Resource Resource	level -	-	-	Research Validation Research	China
Huber, et.al., (2015) [49]	Computing International Conference on Subject-Oriented BPM	NAR, Metric-based and Pattern opti- mizing	Control-flow and Time	-	Transport	Weka, Co- CaMa	Proposal of Solu- tion	Germany
Zhao, et.al., (2016)	Knowledge and Infor-	NRR, Metric-based	Resource	Case	Healthcare	-	Validation	China
[73] Arias, et.al.,	mation Systems International Confer-	NRR, Metric-based	Resource	level Process	Sales/ marketing	ProM	Research Validation	Chile
(2016) [65] Sindhgatta, et.al., (2016) [75]	ence on BPM International Conference on Advanced	NRR, Pattern opti- mizing	Control-flow and Resource	Process level	Car repair and mainte- nance Volvo IT Belgium	-	Research Validation Research	India, Australia
	Information Systems Engineering				process (BPIC 2013			
Zhao, et.al., (2017) [57]	Information Systems Frontiers ACM International	NRR, Metric-based NAR, Metric-based	Resource Control flow	- Process	Sales/ marketing Healthcare	- Java	Validation Research Evaluation	China
Yang, et.al., (2017)[60]	Conference on Knowl- edge Discovery and Data Mining	and Pattern opti- mizing		level			Research	
Schobel et.al., (2017) [52]	In Advances in Intel- ligent Process-Aware Information Systems	NRR, Metric-based	Control flow	-	E-commerce	Matlab	Evaluation Research	Germany
Terragni, et.al., (2018) [54]	International Conference on Future Internet of Things and Cloud	NRR, Metric-based	Control flow	-	Web-based application	Disco	Evaluation Research	the Nether- lands
Seeliger, et.al., (2018) [53]	Workshop on Interac- tive Data Exploration and Analytics	NAR, Pattern opti- mizing	Control-flow, Time, Data, resource	-	Sales/ marketing	ProM	Validation Research	Germany
Pereira Detro et al., (2020) [58]	Enterprise Informa- tion Systems	NAR, Pattern opti- mizing	Control flow	-	Healthcare	ProM	Evaluation Research	Brazil
Park, et.al., (2019)[69]	International Conference on Process Mining	NRR, Metric-based	Control-flow and Resource	-	Financial	-	Validation Research	South Korea
Dees, et.al., (2019) [74]	International Conference on BPM	NAR, Risk mini- mizing	Control flow	-	Insurance	Sci- kit learn	Validation Research	Germany
Weinzierl, et.al., (2020) [55]	International Conference on BPM	NAR	Control flow	-	Sales/ marketing	Tensor flow	Validation Research	Germany
Weinzierl, et.al., (2020) [56]	Hawaiian Interna- tional Conference on System Sciences	NAR, Metric-based	Control flow	-	Web-based application	Tensor flow	Validation Research	Germany
Ghazaleh Khoda- bandelou (2013) [79]	PhD Thesis	Université Panthéon-		1		1		
Irene Teinemaa (2019)	PhD Thesis	University of TARTU	, Estonia					
Sen Yang (2019) Alessandro Ter-	PhD Thesis Master Thesis	Rutgers University, 7 Eindhoven university		e Netherland	s			
ragni (2018)		unanoven university	tccmology, th	- 1.comertand	-			

the focus is on whether the approach considers the control-flow perspective (next activity recommendation) or the organizational perspective (next resource recommendation) to make a recommendation. Moreover, recommendation strategies consider whether the recommendation production strategy is of pattern optimization, risk minimization, or metric-based.

## 4.1.1 Next Activity Recommendation (NAR)

By having a particular partial trace that reflects the process instances' current state, users can select which activity should be executed next. This selection is challenging because process performance objectives (e.g., minimization of running time) should be of concern. It is evident that users with little experience have more difficulties during the process execution, and this may lead to having unfinished process instances [30]. In this context, when the users are unfamiliar, recommendation support is essential during process execution.

NAR methods, according to the type of recommended element, can be divided into (1) single activity recommendation [30, 3, 11, 14, 20, 27, 32, 52, 58, 70, 73, 77, 83, 84, 94, 71] and (2) multi-activity recommendation, named trace or path recommendation as well, initially recommend all the possible steps at once [19, 79, 88]. The path recommendation problem in the multi-process instance environment is yet to be addressed.

## 4.1.2 Next Resource Recommendation (NRR)

The NAR techniques merely consider the control-flow perspective and provide recommendations about the next possible steps, with no idea about the next resources. The resource is an essential index in business process performance. Concerning the application area, resources can be equipment, human resources, money, or software systems that perform the business process activities [31].

Resource allocation, known as staff assignment, is considered necessary in BPM. The proper allocation of the most appropriate activity would lead to effective process performance and efficiency, service level, resource utilization, and reduce execution costs [9]. There are many resource assignment mechanisms in the BPM literature [44, 5, 85]. Still, focusing on actively recommending resources by applying the workflow information is rare.

NRR methods analyze resource-related data, manage execution activities of a business process and assure that the right resources are assigned to the right tasks at the right time. Based on the application environment, NRRs can be divided into single instance resource recommendation [43, 31, 8, 15, 54, 42, 55, 72, 92] and multi-instance resource recommendation. However, the resource recommendation problem in the multi-process instance environment is still not well solved.

The two research approaches proposed by [11, 53] cover both the NAR and NRR approaches. In these studies, both the best next activities in handling

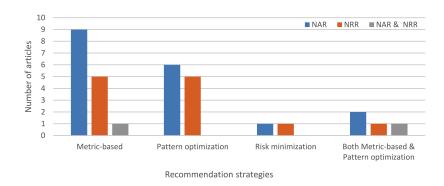


Fig. 4 ARecommendation approaches and strategies about PARSs

a new process instance and recommendations on resources to assist in the resolution of the instance, are applied.

## 4.1.3 Recommendation strategy

Based on the reviewed articles in the PARS domain, another classification is compiled according to the strategies applied for providing recommendations. The first recommendation strategy is the *metric-based strategy*, where goal-supporting activities or resources are recommended as the pre-defined goal optimization (e.g., reducing cost or cycle time). In most studies run on NAR approaches [71, 30, 3, 11, 20, 58, 70, 77, 83, 84] and in some of NRR approaches [94, 8, 55, 92, 93], this strategy is applied.

The second recommendation strategy is the *risk-minimizing* strategy, focusing on risks concerning metric deviations formulated as a mathematical problem. Such studies focus on potential risk reduction during process execution and support users in making risk-informed decisions. If the process instance is executed in such a manner, the likelihood and severity of an error occurrence are calculated. An alarm may be activated in a running instance to intervene, mitigate or inhibit the improper outcomes and reduce cost. Only two articles study this issue [15, 18].

The third recommendation strategy is pattern optimization strategy which includes pattern optimization, statistical and data mining techniques. This strategy is implemented in two steps, i.e., discovering traces of executed instances and then matching them with a running instance. This strategy is applied in six studies in NAR [14, 27, 52, 73, 19, 79] and five studies in NRR [43, 31, 42, 72, 75] approaches.

Both the *metric-based* and *pattern optimization strategies* are addressed in four articles [32, 88, 54, 53]. The classifications of all studies based on recommendation strategies and approaches are shown in Figure 4.

#### 4.2 Process perspective and contextual information

The process perspectives are divided into the following four categories. The focus of the *Control-flow perspective*, is on the process activities order, and applied in 66% [71, 30, 11, 14, 20, 27, 32, 52, 58, 70, 73, 77, 84, 19, 79, 88, 15, 42, 55, 53, 18, 75]. The *time perspective* focuses on the execution time and frequency of activities, analyzing bottlenecks, waiting time, and predict the remaining time of running instances, applied in 15% [3, 32, 73, 54, 15]. The features of instances that constitute the *data perspective*, is applied in 10% [58, 73, 72]. The *organizational perspective*, focuses on the collaboration and relation between resources, is applied in 47% [43, 11, 27, 58, 73, 94, 31, 8, 15, 54, 42, 55, 72, 92, 53, 93, 75].

All perspectives are considered by the authors in [73]; the control-flow, resource, and time perspectives are considered in [15]; while the control-flow, resource, and data perspectives are considered in [58]. Moreover, control-flow and resource are reflected in [11, 27, 42, 55, 53, 75].

The process mining should be contextualized [73, 80]. It means that it is required to extend the scope of PM and extract more insights from the event log. Context is defined in [51] as any information reflecting the changing circumstances during a business process's execution. Based on the literature review made here, studies usually consider the instance and activity attributes. Some of the PARSs only focus on the instance level [14, 27, 88, 15, 72, 93, 34] and just a few on process level information [8, 75]. Recently, a meta-model is defined based on a process cube, which consists of context entities and context attributes [8]. Context entities are connected through the context relationships, though none distinguishes the impact of external factors in the process.

## 4.3 Data type and application domain

The reviewed articles can be classified according to the type of applied data. The methods are assessed through the three types of event logs: (1) real-life logs (i.e., extracted from real-life process execution), (2) synthetic logs (i.e., generated through simulation or replaying a real-life model), and (3) artificial logs (i.e., generated by replaying an artificial model). It is revealed that most methods, 24 out of 33 are tested through real-life logs [1, 71, 27, 32, 58, 70, 73, 77, 84, 94, 19, 88, 31, 8, 15, 54, 42, 55, 72, 92, 93, 18, 75, 34]. Among them, two approaches in [54, 75] are further tested against synthetic logs, while one [55] is tested against artificial logs. Four approaches are tested on synthetic logs [3, 14, 20, 53], while five articles are tested on artificial logs only [71, 30, 11, 79, 72]. Nine articles have applied the publicly-available logs instead of the private logs, which prevent the replicability of the results because they are not accessible. The details on these event logs are expressed in Appendix.

PARSs have been applied in application domains to address varying problems. As to the application domains in the real-life logs, it is found that a set of the logs introduced by the Business Process Intelligence Challenge (BPIC) are applied by 6 studies. The BPIC, as part of the BPM conference series, is held on an annual basis. These logs are publicly available through the 4TU.center repository of Eindhoven University and cover domains like purchase order handling process (BPIC 2019) applied in [83], Employee Insurance Agency (BPIC 2016), applied in [15], Dutch financial institute (BPIC 2012, 2017), applied in [54, 55], and Volvo IT Belgium process (BPIC 2013), [75].

Next to these publicly available real-life logs, a range of private real-life logs originating from different domains like healthcare [19, 88, 31, 93], insurance company [15], manufacturing [27, 94, 42], web usage data [14, 20, 73, 77, 84], IT service continuity management [53], ACM system [32] and helpdesk process [83, 8] are applied as well. Publicly available synthetic event logs like repairing telephone, car repair, and maintenance are applied in [54] and [75], respectively.

The details on application domains identified and the count of studies implemented for each are presented in Figure 5. In this figure, the highest count of the studies belongs to sales/marketing [73, 84, 94, 8, 54], web-based application [14, 77, 83] and healthcare [88, 31, 93]. Because PM is an emerging discipline and has not yet been applied in all fields, this section aims to reveal the potential applicabilities in different fields and encourage researchers to explore these applications in the future.

## 4.4 Implementation types

Many PM tools exist through which the event logs and other data generated by the processes are analyzed. About 30% of methods are declared as being integrated as plugin or standalone tools on top of the ProM framework [71, 30, 3, 52, 58, 73, 19, 8, 54, 34]. ProM is a pluggable, open-source framework that allows the development of new PM algorithms.

The authors in [11] and [15] provide stand-alone plugin implementation on top of ConDec and YAWL<sup>8</sup>, respectively. ConDec is a tool that proposes an open set of constraints for the high-level templates between BP activities and YAWL is a business process modeling language based on the workflow pattern and Petri nets. A plugin on top of CoCaMa, an ACM<sup>9</sup> software solution, developed in [32].

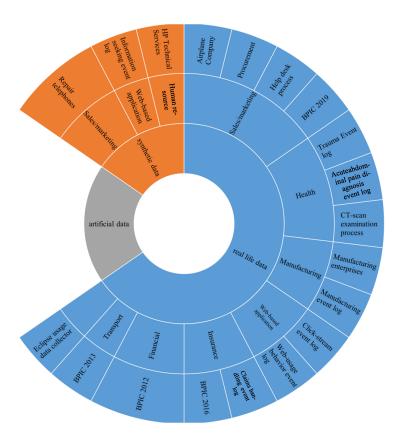
The method proposed by the authors in [77] is implemented as a standalone application using the Disco tool [29], an easy-to-use process mining tool with a friendly interface design. The implementations of other articles are as a stand-alone tool in Java [88] and Eclipse environment [53, 34], through Python [83, 84, 18] and in Matlab [70].

Data analysis solutions have been applied mostly in NRR methods. Weka is applied in NRR cases [43, 31, 42, 72] and next to process analysis tools in NAR methods [15, 32]. RapidMiner is applied only in one NRR case [27].

In 20% of studies run by [14, 77, 94, 55, 92, 93, 75], there exists no declaration on any further explanation on implementation environments, next to

<sup>&</sup>lt;sup>8</sup> Yet Another Workflow Language

<sup>&</sup>lt;sup>9</sup> Adaptive Case Management

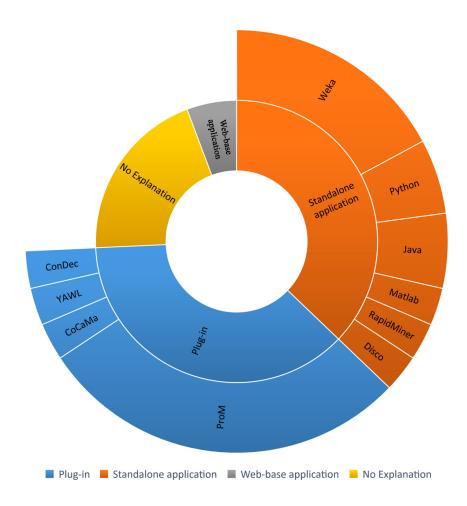


 ${\bf Fig.~5} \ \ {\bf The~categories~of~methods~applied~per~application~domain}$ 

two articles implemented as a web-based prototype without any further details [20, 79]. The implementation environments are shown in Figure 6.

# 4.5 Evaluation methods

Researchers in [86] sought to organize articles through classified research methods based on evaluation criteria in the three categories, i.e., proposal of the solution, validation research, and evaluation research. Validation research was applied to 60% of primary studies to evaluate the proposed model. The assessment is run by doing experiments through simulation or synthetic data, prototyping, mathematical analysis, and mathematical proof of properties. It indicates an increase in the volume of studies with validation of the approaches through experiments where synthetic data are applied. 20% of the primary studies have evaluation research, where the assessment of a proposal or implementation of a proposal is run by applying real scenarios and analyze



 ${\bf Fig.~6}~{\rm Different~implementation~environments~that~are~used~in~the~PARS~studies$ 

the process owners' potential benefits. 20% of the primary studies are classified according to the proposal of solution type. They propose a new solution technique without a full-blown validation accompanied by a simple example of a sound argument. It can be deduced that the proposed PARS approaches are often validated through prototyping, experiments, and applying synthetic data, with less tendency to the practical implementation of a solution regarding case studies.

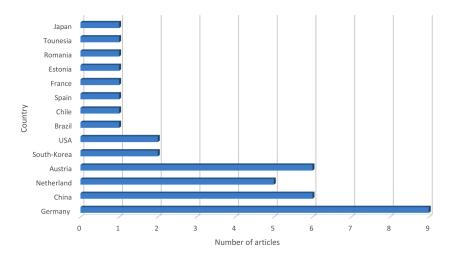


Fig. 7 Publication frequency by country

## 4.6 Geographical analysis

This type of analysis would contribute to determining the distribution of different research clusters at a global scale and identifying the international research groups dedicated to this particular research area. In general terms, the 33 studies were produced by 104 authors from 40 research institutions located in 15 countries. To run a detailed analysis on the premise and the authors' with the highest count of articles on process mining, only the most productive ones should be of concern.

- In 15 countries, the case studies of PARS approaches are evident. The countries with the highest publication frequency are ranked, as shown in Figure 7, are Germany, Austria, China, and the Netherlands.
- Among the research groups assessing the PARS research area, Department of Mathematics and Computer Science, Eindhoven University of Technology, the Netherlands, with five studies, the Software School of Fudan University, China and the Department of Computer Science, University of Innsbruck, Austria, with three studies each are outstanding.
- Overall, 104 researchers have writing 33 studies, where Prof. van der Aalst with five studies, and Prof. Weber, Dr. de Leoni, and Prof. Weidong Zha with three studies each are the most active researchers in this field.

The publications' geographical analysis corresponds to that of the top research groups in the PM field at a global scale. Next to the known researchers appeared through process mining-related publications also match with these groups.

#### 5 Discussion

This article aims to integrate, analyze, and synthesize the proposals available in PARS research. By applying research questions in assessing the particular aspects of process-aware recommendation research, a classification framework is established to analyze 33 primary studies obtained through a systematic search. In the following, we first discuss some challenges in terms of PARSs, and afterward, some research gaps will be discussed.

#### 5.1 Evaluation issues

Comparing performance in different approaches in publications makes it impossible to interpret and determine the most appropriate approach. According to [6], the no free lunch theorem holds regarding search and optimization because no single optimization algorithm performs best in all situations. It illustrates that determining the most appropriate method depends on the customized data set, the application domain, different experimental settings, and the contextual factors, indicating that no comprehensive comparison of the performance values can be made among all studies.

There exists no scientific measuring tool applicable in a direct comparison of the different PARSs. In this context, the count of distinguished proposals' empirical comparison in terms of performance is few. Selecting a proper assessment method highly depends on the objectives that a proposal concerning, the type of techniques and/or data applied for a recommendation. Though the existing PARS methods are objective-oriented, some studies have applied different event logs, experimental settings, assessment measures, and baselines, which has led to a situation with no possibility of exhaustive comparison in a methodologically and experimentally manner. This fact makes the researchers rely only on the potential optimistic impressions expressed in the respective articles.

The lack of a clear framework for prescriptive monitoring techniques and/or universal measures to calculate the accuracy and validity of recommendations is another limitation recognized in this review study. It indicates that each assessment method's efficiency and applicability depend on the proposed technique therein. These issues reveal a degree of PARS studies' immaturity in implementing a standardized methodology for the assessment. Developing an integrated framework and applying more universal accuracy metrics applicable in all PARSs is a potential objective of future works.

In reviewing this literature, it is revealed that the details on experimentation are superficial and are not elaborated on the implementation environment. Moreover, the assessment methods are not explicitly stated in some studies. If this were not so, then the comparison therein would have been easier. Somehow, such studies have obtained good results, but there exists the doubt that due to author's bias, some results with low quality are not disclosed. For this purpose, some standard event logs are required for bench-

marking, which will be proven to add value to the proposed methods. Only 40% of the applied event logs are publicly available in this review study, 4TU ResearchData<sup>10</sup>, and PODS4H<sup>11</sup>, allowing for the studies' reproducibility. About 75% of this 40% belong to real-life processes and make the validations of algorithms through real-life event logs more reliable and more substantial. Because artificial event logs do not necessarily reflect the complexity, variation, and unbalanced class distributions of real-life logs. Everything can be accomplished based on the synthetic data, while researchers must make sure that their simulated data reflect the actual process corresponding to the newly designed algorithm. Hence, we suggest evaluating algorithms on both synthetic and real-life event logs whenever possible. One of the important issues in future studies could be the focus on creating and sharing a collection of publicly available event logs that can be analyzed from multiple perspectives, especially in the operational support task.

Furthermore, in almost all the studies, it is assumed that the system will work as it is after the recommendation. However, as shown in [18], there is a possibility that the outcome of applying the recommended direction would not lead to the expected results. To overcome this challenge, utilizing the process-aware simulation methods at detail [66] and aggregated levels [60] besides PARS would be contributive. Using such approaches gives us this opportunity to evaluate the effect of the actions and measure the system's behavior after applying the recommendations.

#### 5.2 Size and cleanness of data

Increasing recorded data in information systems gives a higher potential to apply recommender systems. However, by increasing the size of data and the number of attributes, more hardware requirements and time are needed to provide a suitable PARS. In some scenarios, it is impractical to apply some of the existing methods using standard hardware. Moreover, in many real-life applications, data contain noise/outlier [67] and uncertainty [56], leading to imprecise recommendations.

The available PARSs are based on structured data for offline solutions, while the potential and challenges of such recommendations regarding big data scenarios with active process instances are yet to be assessed. Only a few works provide semi-online/real-time recommendations [53]. Applying and scaling PARSs on big data scenarios and stream processing is a promising research theme. These big data tools can present solutions to applied problems and introduce new inspiring challenges for further research. The developing models capable of handling complex data for assessing real-life problems will be developed.

To overcome this challenge, one can adopt the current algorithms to work for big data scales and benefit from parallelization methods. Moreover, it is

<sup>10</sup> https://data.4tu.nl

<sup>11</sup> http://pods4h.com/pods4h

possible to reduce the size of data by wisely apply both domain-based and statistical pre-processing methods, e.g., sampling [68] and clustering [49], before the recommendation to improve both the quality and performance of the final result. To handle active instances in a more efficient time, PARS can benefit from algorithms that work for streaming data [91, 13].

#### 5.3 Considering contextual information and frequent factors

In most realistic scenarios, numerous factors can affect the process, which should be considered in a PARS. A more challenging part is that different factors from different layers are available that affect each other in many of the cases. For example, the amount of workload can affect the speed of resources in the process such that up to a specific amount of tasks, resources perform better. Other factors such as new regulations or new advertisement methods can affect the number of new customers/users in the processes/systems. To deal with this challenge, one can propose using methods that can consider lots of parameters and their inter-connections [60]. Using this approach, different effective factors of the processes are extracted, and the relations between these factors and the external factors are modeled.

The analyses here indicate that in most of the available studies, it is assumed that the process does not change in due time. Consequently, researchers do not estimate the impact of external factors and human behaviors in the process in a holistic perspective. It is observed that the contextual factors and different levels of abstraction are often omitted from prediction and recommendation aspects in PM. These proposed techniques have a common drawback, i.e., providing retrospective analyses and non-consideration of the environmental and external factors highly contributive in the process execution.

Though some studies have sought to consider contextual information, they tend to assess the trivial insight by only focusing on the process at a low-level of abstraction, thus, disabling in long-term predictions. Capturing different levels of abstractions and contextual information would generate more informative trustworthy recommendations. According to [48], context information can improve the prediction quality as it adds valuable information to the predictive module. Consequently, analyzing just one model cannot produce a panorama on the relationships between resources and activities in a process.

Analyzing the impact of some factors, like the effects of process changes, rich information hidden in human behavior, and dynamics in an ad-hoc environment in detail is a must in this area. The reason is that PARSs require extensive knowledge on business processes for long-term predictions considering multi-classes based on a context, outcome, or process variant. Recommendation(s)' quality is subject to the quality of the event logs and the discovered process model(s). The new techniques through which abstract views are generated on an organization in a process perspective based on instance data are considerably informative for top management if they provide performance insights.

Customizing recommendations is an understudied essential theme. PARS must correspond to the users' profiles by learning their context and recognizing their objectives to generate recommendations proactively. Therefore, future research could deal with the proactivity and personalization challenges when developing recommender systems based on PM. Furthermore, in most applications, providing completely automated recommender systems is inapplicable. For example, it is possible that some parts of a recommendation are not practical according to the business of the process. One way to deal with this challenge is providing interactive solutions and letting users apply their business knowledge interactively within the PARS.

#### 5.4 Recommendation type

This study revealed that algorithms could be categorized according to the two main types of recommendation approaches of NAR and NRR. Among 33 articles, 19 are of the NAR category and 12 of NRR, and two are both. It is found that the path recommendation in the NAR category, a multi-resource recommendation in the NRR category, and recommendation in the multi-process instance environment of both categories are not assessed well yet. Process path recommendation of this type allows instance service organizations to improve customer satisfaction or detect unexpected termination(s). The importance of recommending multiple resources is important when a recommended resource is overloaded, and many instances are waiting in a queue for resource release.

As to the recommendation strategies, three proposed models have focused on the process-aware recommendation issue through risk-minimizing; 14 proposals are related to metric-based and 11 proposals to pattern optimization. The risk-minimizing strategy is of less concern in these proposals. Risk-aware decision-making allows companies to detect and effectively manage the process instances to avoid the inappropriate effects of unexpected outcomes. When risk elimination is not feasible, process-related risk reduction and management become important.

#### 5.5 Application domain and supporting framework

In this review study, the existence of tool support is of concern in determining whether it is a stand-alone application or a plugin in a broader platform. Such proposals with tool support help companies easily apply, assess, and understand the applicability, efficiency, and potential results of PARSs.

A general multi-domain systematic study is conducted in [69], to map the applications of PM. They identified 19 application domains, and for the top six areas, i.e., healthcare, ICT, manufacturing, education, finance, and logistics, they described the main contribution of PM. In this review study, we found that PARS approaches also have been applied in different domains. As stated in Subsection 4.4, sales/marketing, web-based application, and healthcare domains are the most active in this context. The algorithms for PARS

are not limited and can be applied in new domains where the event log can be recorded. It would be of interest, especially for emerging smarter application domains where event logs are collected through sensors and contain behavioral and environmental data like the smart city, smart health, and smart grid. These domains are subject to new planning, execution, monitoring, and adapting process instances, because of the sensors, actuators, connectivity and analytics integration.

In financial technology, the PARS techniques have potential application. The rapid growth and pervasive application of financial technologies have endangered the financial industry against different cyber-crime forms. Consequently, the financial services must resort to new advanced technologies therein to detect and prevent these fraudulent acts. This issue makes researchers reassess the application of risk-minimizing PARS techniques in this industry. PARS techniques can be applied in predicting an individual's digital identity and detecting his/her fraudulent connections, and sound the alarm therefor. This new area of research seems to carry a broad set of promising unexplored aspects.

## 5.6 Responsible PARS

With the advancement of data science techniques and the abundance of data, their applications and influences on human life expand profoundly. Their techniques are already applied in various fields, including life sciences, smart cities, transportation, and business intelligence. The huge influence of data science on human, make the hazards of data science without ethical considerations apparent. Disclosure of personal and confidential information and prejudice in the form of implicit bias in automated decision-making are two of the main risks of the irresponsible use of data science. These hazards have already been addressed and studied intensively in the area of data science, which results in methods and techniques that are compliant with ethical requirements by design. Moreover, in the area of PM, ethical issues have recently received attention.

Two of the most important aspects of responsibility in PM are fairness [61] and privacy [62]. In a fair PARS, the focus is on avoiding unfair recommendations (e.g., false or biased conclusions), even if they are accurate. In other words, For example, we should not consider the gender/religion/color of an applicant in a recommender system that works on top of a company's employment process. To consider privacy-preserving, a PARS should consider private and confidential data into account. According to plenty of regulations, such as GDPR<sup>12</sup> [82], companies and information systems are obligated to consider individuals' privacy while analyzing their data. Therefore, it is necessary to consider which data attributes are stored by the PARS. Moreover, it should be considered which information can be revealed from the output of PARS

 $<sup>^{12}</sup>$  General Data Protection Regulation

that can conflict with privacy policies. These issues in PARSs are yet to be addressed.

## 6 Threats to validity

According to the researchers in [57], threats to validity are influences that may limit our ability to interpret or draw conclusions from the study's data. They are of four main types: construct validity, internal validity, external validity, and reliability addressed here to be minimized in this literature review.

- 1- Construct validity focuses on the relation between the theory behind the experiment and the observation(s). It reflects to what extent the operational measures that are studied represent what the researcher has in mind and what is investigated according to the research questions[87]. Accordingly, to minimize these threat types, combining the process mining and recommendation terms is well established to define a sufficiently stable search string. The count of articles found herein indicates that the search terms were well defined and reported. To reiterate, only available data between January 2008 and September 2020 are considered.
- 2- Internal validity is related to the classification of each article according to the data collected by the authors.
- 3- External validity is concerned with to what extent it is possible to generalize the findings and the extent of their interest to other people outside the assessed case [87]. In general, the obtained results are generalized and limited to the research period and the approaches published in the research area of recommendation systems and process mining disciplines. In this context, both the process mining and recommendation communities can benefit from this review's findings. In this regard, we included only published peer-reviewed journal/conference articles.
- 4- Reliability relates to data collection and the analysis thereof to gauge whether it was conducted in a way that others can repeat with the same results [7]. To maximize this goal, in this literature review, the guidelines outlined in [37] are applied, and the procedure is described in a level of detail that is sufficient to replicate the search. The search terms are defined according to a standard procedure.

One of this study's validity threats refers to the potential selection bias and inaccuracies in data extraction in the literature review. The well-known literature sources and libraries in information technology are applied to extract the relevant works on the PARS topic by running chain searching to avoid the exclusion of potentially relevant papers.

Another potential bias is the subjectivity in applying the inclusion and exclusion criteria according to determining the subsumed studies. To mitigate this threat, each article is independently assessed against the inclusion and exclusion criteria by all the authors.

Another source of reliability threat is related to the count of returned records during the study period (i.e., from 2008 to 2020) because some articles can be registered in such databases only a few months after their publication. Consequently, some articles presented at the end of 2020 are not returned to our search pool. Researchers may produce different results as the search and ranking algorithms applied by source libraries are updated (see, e.g., Google Scholar).

#### 7 Conclusion

This systematic review provides a solid foundation for future research on process-aware recommender systems. According to this survey, a limited number of studies exist where the PM improvements are applied for developing intelligence-based approach in making predictions about process outcomes, alarm generation for anomaly detection, and next activity/resource recommendation. During the past 30 years, PAIS research has focused on the core PAIS-relevant features' design like implementation, function, and application, with no concern on experience and feedback therein. It indicates that applying prescriptive analysis during the PAIS development has not been the main focus. To be able to use more beneficial analysis, the future research trend in PM should divert from pure descriptive analysis towards prescriptive analysis.

No extensive systematic review study is conducted on the articles already published about PARS, which means the specific and new area between the PM and recommender systems' intersection. In this article, we have followed a protocol of conducting review studies to create an initial classification of the publications in this research area, something not considered in the available studies. This classification framework can be applied by researchers if obtaining a more comprehensive perspective on the theory and application of PARS. Such classification can support researchers involved in both the process mining and recommender systems to understand each other better to contribute to the development. This study answers the following questions:

- (1) The trend of the published articles about PARS. The scope of this review covers 33 primary studies from 2008 to 2020 that have been published across journals (32%), followed by conferences (58%) and dissertations (10%), next to other inclusion and exclusion criteria. During the 12 years, half of these studies have been disseminated in the past five years, which may indicate an upward trend in using PARS. Note that PARS is an active research area despite the prevailing limitations, and attempts should be made to keep pace with the ongoing advances made in this area.
- (2) The common characteristics of the studies in which recommendation techniques are being applied to PM. As to the second research question, it was possible to delineate a picture of how the primary studies are distributed in terms of the type of recommendation methodologies, evaluation, geographical areas, and application domain aspects.

Regarding the second question, 55% of studies belong to NAR, and 41% of studies are metric-based. The most frequently applied process perspective is the control-flow (67%), and few studies have considered contextual information (26%). The publicly available event logs are applied in 40% of studies, where only 30% are developed based on the ProM framework. Evaluation methods of 56% of studies are based on validation research. It indicates that approaches are not only validated using experiments that apply synthetic data and the implementation of prototypes but through the case studies as well. The increasing trend of case studies as an evaluation method promotes the maturity level of the research area. This greater maturity level, in turn, will require researchers in the future to assess their proposals in real environments.

One of the main concerns in this review study is to find out to what extent the recommender systems algorithms and techniques would be applied in process mining, considering that both techniques are widely used in data science. To the authors here, in this context, although research in process mining is on rapid growth, little relevance is given to the recommendation problem, possibly due to a relative lack of knowledge about the potential benefits of such technique for process related-problems. An attempt is made to contribute to a change in this realm by publishing this review. The results obtained here confirm that the task of activity/resource recommendation is an emerging research area, and has attracted attentions over the last five years.

According to this study's context, it is deduced that there is no applicable comprehensive process monitoring solution. A general model for the process-aware recommender system is yet to be proposed. An ideal PARS model should consider the contextual information and the impact of some factors, like the effects of changes in process, interpretability, and handling the great volumes of event logs in near-real-time.

## Appendix: Details about event logs used in PARS

## - BPI Challenge event logs

BPIC 2012 (Dutch financial institute event log): The information of this real-life event log includes the process for a personal loan or overdraft in a global financing organization. This log was gathered from October 2011 to March 2012 and contains 13,087 cases and 262,200 events [54, 55]. BPIC 2013: This event log is from Volvo IT Belgium and contains events from an incident and problem management system named the VINST. The data is separated into the three: 1- Incidents, a log of 7554 cases containing 65533 events related to the incident management process, 2- Closed problems, a log of 1487 cases containing 6660 events related to closed problems in the problem management process, and 3- Open problems, a log of 819 cases containing 2351 events related to open problems in the problem management process event logs [75].

**BPIC 2016:** UWV is a Dutch governmental employee agency that provides financial support to Dutch residents who have lost their jobs and seek new employment. The data in this collection relates to the 300,000 applicants over a period of 8 months [18].

BPIC 2019: This data is from a large multinational company operating in the coating and paint industry in Netherlands. There are collected over 1,5 million events of purchase orders submitted in 2018. The event log includes a total of 76,349 purchase documents containing a total of 251,734 items. Totally it contains 1,595,923 events relating to 42 activities performed by 627 users. Each case has the following attributes: name, purchasing document, item type, goods receipt, source, doc. category name, company, spend classification text, spend area text, sub spend area text, vendor, name, document type, item category [83].

# - Other publicly available event logs

Eclipse Usage Data Collector (UDC): is a system where the information on how do the developers apply the Eclipse platform is collected to generate event logs. The event logs are uploaded to servers hosted by the Eclipse foundation, which contains 1,048,576 event logs from over 10,000 Java developers between September 2009 and January 2010 [35].

Repair telephone process: This synthetic event log is related to a process in a telephone service repairing company, with 1104 cases and 11855 events. The minimum and maximum length of each trace is 4 and 25, respectively [54].

Help desk process: This dataset contains events from a ticketing management process of the help desk of an Italian software company. The process consists of nine activities: case ID, sub-process group, process typology, resource, cost, customer satisfaction, creation date, closing date, and priority. All cases begin with the insertion of a new ticket into the ticketing management system, and end when the issue is resolved. This event log contains 3804 process instances and 13710 events and it is available at https://data.mendeley.com/datasets/39bp3vv62t/1 [83, 8].

## - Not publicly available event logs

HP technical services process: This synthetic event log is gathered within an HP R&D project on next generation IT service management solutions. More than 250 cases, related to issues in a human resource software application and incident management are collected. There are 4 types of cases, each including information like: case type, title, tags (a set of keywords that are attached to the case), step (activity), step flow (trace), participant, case status (draft, open, closed), priority (severity level of the issue) and contextual information on people interactions [53].

Information seeking process: This synthetic data is applied in recommending optimized information seeking process to users and is divided into two separate parts: 1) User features, describing: keyword, web page, tag, access time, access date and location, and 2) Web page features describing: relation of tag/ tag category/ keyword and web page. This part contains information about seeking process start, seeking process end and successful seeking process. [14]

CT-scan examination process: Radiology process collected from Chinese Huzhou Hospital's radiology department within 2009-06-01 to 2009-06-30 period. This real-life event log includes 244 cases and is not publically available because of patient privacy issues [31].

Claims handling process: The not publicly available event log of a large insurance company recorded over one year containing 1065 traces [15].

Manufacturing process: This data is collected from a motor car shock absorber manufacturing factory with an event log containing 100,000 process instances[27].

Acute abdominal pain diagnosis: This real-life event log is of the experiments run within 2009–2010 and contains 11,490 cases. The total count of events is 80,430 where 82 employees participated in the process execution. The case ID, resources, cost, beginning and ending time are the data recorded for each task [93].

Airplane airline: This event log contains a total of 2262 customer compensation data from a Shanghai airline. The data contains the count of customers for compensation, application time, compensation process operators, tickets ID for compensation, etc. [94].

Trauma process: Three medical event logs are collected from the emergency department of children's national medical center, a level 1 pediatric trauma center in Washington, DC. Tracheal Intubation event log with ten context attributes: 1) Patient demographics (age, gender, BMI, injury type, injury severity score, pre-arrival intubation, mental status, body region injured), 2) Provider attributes (incubator's medical role), 3) Event attributes (emergency/pre-arrival, direct-laryngoscopy/video-laryngoscopy and reason for incubation) [88].

Click-stream process: The data has click-stream information of 2 million users in a time frame of one month, with 10 million events [84].

**Procurement process:** This data is extracted from a SAP ERP system for procurement of goods in one month. It contains 33277cases, 255427

events, 37 items and 15 case attributes describing which good was ordered or which vendor delivered the order [73].

Web-usage behavior process: includes web usage behavior data of the customers from a financial service provider. The event log consists of a case ID, click ID, time stamp, and six context attributes. The data set includes 2,142 traces with a maximum length of 247 clicks [84].

Manufacturing enterprises: This real-life event log is collected from three manufacturing enterprises, each containing three types of information: workflow history information, workflow model definition, and organizational information. Xiamen KingLong United Automotive Co. Ltd., contains 256 activities, 179 resources, and 10808 event entries; Hebei Zhongxing Automobile Co. Ltd., contains 399 activities, 244 resources and 42099 event entries and Datong Electronic Locomotive Co. Ltd. contains 922 activities, 147 resources and 99756 event entries [43].

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