Predictive Process Monitoring: A Use-Case-Driven Literature Review

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Abstract. Predictive process monitoring is the subject of a growing interest in academic research and industry. As a result, an increased number of papers on this topic have been published. Due to the high complexity in this research area, a poor comparability is given. Several researchers have already tackled this issue by providing different academic categorizations. However, it seems that the needs of the industry are not considered. The situation makes it difficult to identify relevant papers and thus possibilities for collaboration. Therefore, this paper contributes to the knowledge domain by developing a taxonomy of three identified business use cases. First, a wide-ranging systematic literature review identifies research papers in this area. Then a use-case-driven taxonomy is proposed to establish an efficient and fast framework. Finally, the identified papers get categorized based on the meta-data and by reading the full text of each paper. Hence, the papers data will support practitioners and researchers in identifying relevant papers based on use cases.

Keywords: Business Process Management, Predictive Process Monitoring, Process Mining, Systematic Literature Review

1 Introduction

In recent years, organizations have tried to exploit historical process data to get data-driven insights from the day-to-day business operations. One opportunity to improve process performance by exploiting historical data is to train models based on different types of machine learning. Predictive process monitoring (PPM) takes historical process data (a set of completed business process executions) as input and uses machine learning techniques to predict a user specified need during the runtime of a selected business process. In the past, different setups have been applied because of the high complexity. That stems from the fact that researchers have used different algorithms, datasets, domains or prediction goals. Because of the high complexity and poor comparability, a variety of taxonomies for different scenarios have been developed.

In 2017 [28] and 2018 [53], the most representative time prediction setups of business processes were summarized. Even though both papers had the same intention, the methodology differs as shown in chapter 4. Another review in 2018 by [17] tackled the issue of the high variety of techniques and developed a value-driven framework based on prediction type. Finally, [48] presented a categorized collection of outcome-oriented PPM methods to enable researchers to compare methods in a unified setting.

The aim of this paper is to summarize, evaluate and categorize relevant literature based on business use cases (UC). The motivation of this is to provide a simple and easy to understand framework that promotes communication and collaboration between the industry and academia. This is achieved by a systematic literature review (SLR) that identifies published papers and by devising a taxonomy to classify the observations in UC. Further goals are to evaluate the results by means of different dimensions and to provide an overview with references to relevant literature to support practitioners and researchers in their future work.

The paper is structured as follows: the second chapter describes the main terms connected to the PPM area. Section three proceeds the SLR methodology and the review protocol. In sections four, a taxonomy gets developed that categorizes the result of section three. Section five discusses the results of this paper. The final section summarizes the academic and industrial contribution of this paper and identifies topics for future work.

2 Background

2.1 Business Process Management

Business Process Management (BPM) is a set of methods, tools and techniques to see how work is performed in an organization [10]. As a central element of contemporary organizations, BPM can support and monitor processes that are e.g. subject to policies, regulations and laws. The capability to optimize or support business decisions while running on an enterprise resource planning or workflow system is known as business activity monitoring [40]. However, BPM does not provide predictive solutions for a specific running process. That is where PPM comes into play. PPM focuses on exploiting generated process data and provides business insights that allow business users to take countermeasures during runtime.

2.2 Predictive Process Monitoring

PPM aims to predict the future of quantifiable values during a running process execution [25, 50] whereas for example business process intelligence focus on long term predictions such as key performance indicators [32]. To predict the outcome of running processes, PPM exploits historical data of already executed processes of the same type [25]. The set of historical data consists of events that correspond to the execution of activities of each process instance. Based on the prediction of these traces, the idea is to enable the business to proactively improve process performance and mitigate risks [39]. There are many scenarios where it is useful to have reliable process predictions, such as predicting compliance violations [8], the remaining sequence of activities [11, 43] or the remaining execution time of a case [9, 38].

2.3 Process Mining

In recent decades, process mining has emerged as a research field that focuses on analysing the execution of processes. Process mining is a collection of techniques to extract valuable process data [3]. Depending on the BPM lifecycle, different approaches such as process model discovering, monitoring or improving can be accomplished. In this paper the target is to support making decisions during runtime by using logfiles [2]. PPM makes use of process mining by retrieving the information from Process Aware Information Systems (PAIS) that are stored in logfiles for example in order to make time [1] or cost predictions [49].

3 Research goals and method

This paper applies an SLR in order to review a specific area in a thorough and unbiased manner [21]. The review ensures a rigorous and complete documentation and will be used to create a use-case-driven taxonomy that categorizes research papers. Furthermore, in chapter 4 the results will be evaluated and analysed by different dimensions to identify the relevance and to provide an easy access for the industry.

3.1 Systematic Review Protocol

The systematic review protocol specifies the research questions, the search protocol, and the selection criteria. Below, the research questions (RQ) are formulated, electronic databases are identified and inclusion as well as exclusion criteria are defined. The paper aims at answering the following research question:

1. RQ (Existing published papers): “Which types of academic publications exist in the field of predictive process monitoring?”

In line with the main research question, the paper also answers the following sub-research questions:

1. Sub-RQ (Taxonomy): “How should the published papers be categorized?”
2. Sub-RQ (Ranking): “What are the most relevant published papers?”

The first step was to develop search strings that are used to query electronic databases with the goal of producing a broad outcome of academic papers in the area of PPM. The following search strings derive from the terms introduced in chapter 2 and are used as keywords:

- “(business) process” – the domain of the paper is in the area of business processes
- “prediction” or “predictive” – a relevant paper needs to discuss the area of prediction
- “(business) process monitoring” – a paper targets the area of process monitoring
- “process mining” – a relevant paper targets the area of process mining

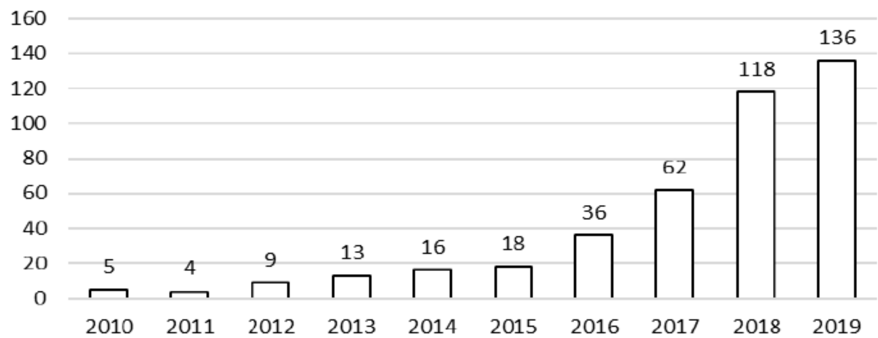
Because the research areas of the keywords “monitoring” and “prediction” or “predictive” are vast and encompass areas outside of the BPM domain, the search strings are always combined with “(business) process” to limit the results in a manageable way. BPM itself can include different angles and different domains. To ensure a broad field of literature and to not limit the search, the keywords “algorithm”, “techniques” and “prediction type” were left out. Presuming that different authors might use a variety of wordings to refer to PPM, the following datable shows all constructed phrases. The generated phrases were then executed by a software that is designed to present cases for research in a structured and manageable way [19].

Table 1. Applied search strings for the SLR to academic databases

Search Strings	Results	Date of Search
“business process” AND “prediction”	51 Papers	07.02.2020
“prediction” AND “business process”	33 Papers	07.02.2020
“prediction” AND “process mining”	17 Papers	07.02.2020
“predictive” AND “business process monitoring”	289 Papers	07.02.2020
“predictive” AND “business process”	316 Papers	07.02.2020
“predictive” AND “process mining”	37 Papers	07.02.2020
“predictive” AND “process monitoring”	248 Papers	07.02.2020

The phrases were applied to the Google Scholar academic database, a well-known electronic literature database in the field of computer science, that encompasses other electronic databases such as ResearchGate, arXiv, Elsevier, IEEE Xplore and Springer. The search was conducted in February 2020 and retrieved all studies that contained at least one of the constructed phrases in the title, keywords, abstract, or full text of the paper. The results were exported and merged into one Excel sheet for further processing. It returned in total 991 papers, 507 excluding duplicates. Duplicate are identified as papers that appeared in more than one search result of a phrase that have the identical title and author(s) [22]. The following figure shows how the studies are distributed from 2010 to 2019. Figure 1 shows that the number of publications on PPM is constantly increasing. Thus, a significant growth of published papers from the beginning of 2016 can be observed.

Fig. 1. Number of published predictive process monitoring papers from 2010 to 2019



In order to be considered the results of the SLR were matched against inclusion and exclusion criteria that are based on the research question. To assess the study's relevance, it then must satisfy all inclusion and exclusion criteria. In this paper the three inclusion criteria were applied in the following chronological order:

1. Inclusion criteria: The paper is cited at least five times (An exception was made for papers published in 2019. Due to the lack of time to get the necessary number of citations it was lowered to three)
2. Inclusion criteria: The paper is written in English
3. Inclusion criteria: The paper was published in conferences proceedings or journals

After applying the inclusion criteria, the number of papers was reduced to 106. The remaining papers were further assessed with respect to the exclusion criteria by viewing the abstracts of each paper.

1. Exclusion criteria: The paper is not related to the computer science field
2. Exclusion criteria: The paper is not concerned with prediction in the context of BPM
3. Exclusion criteria: The paper is not accessible on the web

After proceeding the exclusion criteria, 39 unique papers were kept in accordance with the main RQ. However, literature reviews come with its limitations. Consequently, to have a benchmark the data of the paper gets compared with the findings of other reviews from the same research field. Four different papers that also applied an SLR were identified. Table 2 shows the review methodology and results of each paper.

Table 2. Comparison of papers review methodology sorted by years covered

	Keywords	**Search scope**	**Min. number of citat.**	**Years covered**	**Papers after filtering**
Method in [53]	"predictive process monitoring" "predictive business process monitoring" "predict (the) remaining time" "remaining time prediction" "predict (the) remaining * time"	Title, full text	5 (except 2017 papers)	2005-2017	53
Method in [48]	"predictive process monitoring" "predictive business process monitoring" "business process prediction"	Title, abstract, keywords, full text	5 (no exception)	2005-2017	14
Method in [17]	"predictive" AND "business process" "predictive" AND "process mining" "prediction" AND "business process" "prediction" AND "process mining"	Titel, abstract	10 (if published before 2016)	2005-2018	51
Method in [28]	"business process" AND "prediction" "predictive monitoring" AND "business process"	Title, abstract, keywords	5 (except 2016-2017 paper)	2010-2016	41

	Keywords	Search scope	Min. number of citat.	Years covered	Papers after filtering
Papers method	"business process" AND "prediction" "prediction" AND "business process" "prediction" AND "process mining" "predictive" AND "business process monitoring" "predictive" AND "business process" "predictive" AND "process mining" "predictive" AND "process monitoring"	Title, abstract, keywords, full text	5 (except 2019 papers)	2011-2019	39

It can be observed that the methodology does not vary noticeable in the use of keywords and their combinations. Since different authors might use different terms for the same meaning, it is difficult to identify how the number of search phrases and combinations affect the result of papers after filtering. Besides that, the used inclusion and exclusion criteria and the RQ of each paper can have a strong impact on the result in terms of quantity and quality. That can explain why the numbers of [48] differ considerably from the overall result. Moreover it can be observed that the papers method has a lower result than [28] [17] [53] although more keywords were used.

From the papers final list, standard meta-data such as authors, year of publication and number of citations were extracted. In addition, the type of publication, type of domain (identified by the origin of the data set or log) and type of prediction were extracted by reading the full text of each paper.

4 Taxonomy and data analysis

Usually the literature on PPM can be classified by two main dimensions: type of prediction and algorithm [17]. In this section, a taxonomy is proposed to classify the identified papers by business use cases and thus to answer Sub-RQ1. At the beginning a parent use case describes the need of the paper which correlates to the RQ: "*As the industry I want to have an understanding what relevant academic research exists to identify collaborations in the area of PPM*". The starting point is further broken down in business use cases to identify and organize the need of the industry more in detail. This step is necessary to establish an easy to understand communication basis between the industry needs and academic papers. Based on each use case a subcategory is introduced to provide an efficient and fast overview. For a better understanding, each business use case is elucidated by a brief explanation and further examples. Finally, different academic papers are assigned to the use-case-driven framework and the chapter concludes by presenting results in three data tables.

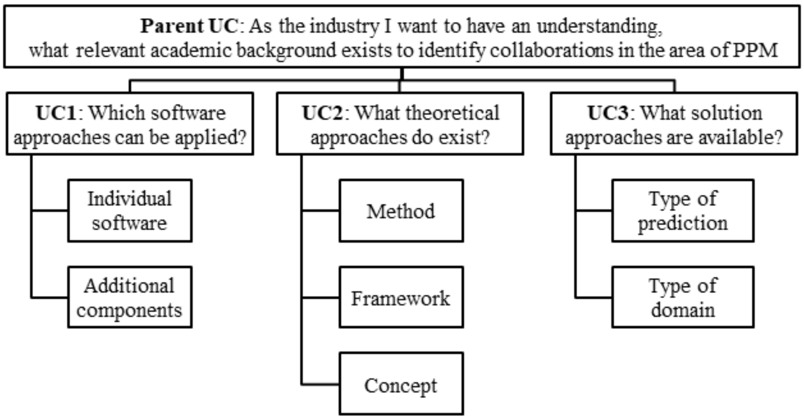
UC1: Which software approaches can be applied? Academic papers that contribute a technical implementation are assigned to this UC. The software solution can include frameworks [13, 16], improvements [12] or fill the gap between research and practice [20]. To ensure an easy understanding on the industry side, the type of implementation is categorized as individual software [20] or as additional component for instance for a mining toolset [13]. Commercial solutions are not taken into consideration.

UC2: *What theoretical approaches do exist?* The use case focuses mainly on a theoretical level by introducing methods, frameworks and concepts. Methods or techniques focus on a particular procedure to fulfil a more general [18, 25] or specified goal [14, 24]. Then again frameworks [17, 28] help to accomplish a goal that can include different methods [15]. At last concepts have a more abstract level of detail and therefore provide a rough overview of thoughts and approaches [37]. The academic contribution often gets confirmed by a case study or review.

UC3: *What solution approaches are available?* The use case aims to tackle a particular problem and proposes solutions. Each solution approach is related to one of the three macro-categories of prediction as outlined in [17]. The solution can provide a theoretical approach that gets confirmed by a set of generated [18, 34] or real life data [31, 35]. Based on the used data set the domain of each paper was specified.

In figure 2 the use-case-driven framework is visualized to provide a better understanding.

Fig. 2. Taxonomy of use cases for predictive process monitoring



Next, the SLR results get categorized by use case. Each paper gets assigned once and is shown in the use-case-driven framework below. The tables are structured from the left to the right as follows: The first column references the academic paper to provide an easy access for the industry. Followed by use case specific subcategories, the number of citations, type of publication and year of publication. All tables are sorted by number of citations to provide a ranking by relevance and to answer Sub-RQ2. As a result, 4 software, 22 theoretical and 13 problem-solution papers are identified.

Table 3. Overview of four software approaches (UC1: Which software approaches can be applied?)

Ref.	Type of implementation	Number of citations	Type of publication	Year of publication
[16]	Addit. component	69	Journal	2017
[20]	Indiv. software	7	Conference	2017
[12]	Indiv. software	7	Conference	2017
[13]	Addit. component	6	Conference	2015

Table 4. Overview of 22 theoretical approaches (UC2: What theoretical approaches do exist?)

Ref.	Type of theory	Domain	Number of citat.	Type of pub.	Year of pub.
[25]	Framework	Healthcare	141	Conference	2014
[31]	Framework	Logistic	100	Journal	2014
[18]	Method	-	99	Journal	2014
[24]	Method	Financial, healthcare	87	Conference	2016
[42]	Method	Customer supp., financial	72	Journal	2015
[47]	Framework	Financial	42	Conference	2016
[28]	Time	-	40	Journal	2017
[43]	Framework	Healthcare	34	Conference	2012
[51]	Method	Healthcare, insurance	32	Conference	2016
[48]	Framework	-	32	Journal	2019
[14]	Framework	Healthcare, public admin.	29	Conference	2016
[27]	Method	Automotive, healthcare	28	Journal	2017
[17]	Framework	-	26	Conference	2018
[15]	Framework	Healthcare, public admin.	22	Journal	2018
[52]	Method	Financial, public admin.	15	Conference	2016
[53]	Framework	-	13	Journal	2019
[26]	Concept	Insurance	10	Conference	2017
[46]	Framework	Financial, healthcare, manufac-turing, public admin.	9	Journal	2018
[44]	Method	Customer supp., financial, healthcare	9	Journal	2018
[4]	Concept	Logistic	7	Conference	2016
[37]	Concept	-	5	Conference	2018
[23]	Method	Manufacturing	5	Journal	2018

Table 5. Overview of 13 solution approaches (UC3: What solution approaches are available?)

Ref.	Type of prediction	Domain	Number of citat.	Type of pub.	Year of pub.
[45]	Sequence of activities	Customer supp., financial, public admin.	137	Conference	2017
[7]	Outcome	-	90	Journal	2016
[35]	Time	Customer supp., financial, public admin.	54	Journal	2018
[11]	Sequence of activities	Automotive, financial	49	Conference	2016
[36]	Time	Public admin.	48	Conference	2014
[41]	Time	Healthcare, manufacturing	30	Conference	2017
[33]	Time	Customer supp., financial	20	Conference	2017
[29]	Sequence of activities	Automotive, customer supp., financial	17	Conference	2017
[34]	Time	Generated Data Set	16	Conference	2011
[6]	Next activity	Financial, manufacturing	14	Journal	2019
[54]	Time	Financial	10	Conference	2017
[5]	Time	Logistic	9	Conference	2013
[30]	Next activity	Customer supp., financial	5	Journal	2018

Following the papers proposed use-case-driven framework, practitioners and researchers can easily navigate through the field of interest with the aim to identify academic papers for further collaboration. To provide an easy and efficient framework each use case provides its own subcategories. Furthermore, papers can get selected by the number of citations and the year or type of publication.

5 Discussion

To review the above contribution, an SLR was conducted to identify relevant research in the area of PPM. In contrast, the study was not limited to a specific type of prediction [48] or methods [28]. The papers taxonomy followed a more generic approach by providing the industry a relevant overview of different business use cases. A similar approach has been done by [17] where the taxonomy guides companies through a selection of prediction goals to find the best technique matching their needs. In comparison, the scope of this paper also includes the software and theoretical perspectives.

Concerning the number of papers after filtering, it is difficult to state if all relevant academic papers were identified. The search result depends heavily on the methodology as introduced in table 2 and the databases that were used to conduct the search. To have a benchmark, the result of papers after filtering for each identified SLR in the field of PPM gets compared by a cross table. An overlap is identified when papers have an identical title and the same author(s). To simplify the result, the overlapping is shown in percentage.

Table 6. Overlapping of literature review results in the search area of PPM

	[53]	[48]	[17]	[28]	**Paper**
Results of [53] in	-	21%	31%	28%	21%
Results of [48] in	12%	-	10%	13%	15%
Results of [17] in	64%	36%	-	56%	44%
Results of [28] in	44%	36%	43%	-	36%
Results of this paper in	32%	43%	33%	36%	-

The comparison shows that the performed review includes at least 30% but always less than 45% of all other review results. The identified gap can be an indicator that not all relevant work is identified and therefore seen as a threat of incompleteness.

6 Conclusion and future work

The research area of PPM has been growing significantly in recent years. However, the high degree of complexity makes it difficult for the industry to find a suitable overview that promotes collaborations. The novelty of this research is, on the one hand, to provide by the means of an SLR a relevant academic background. On the other hand, this paper introduces a new communication approach by providing a use-case-driven framework to guide the industry in an understandable and easy way through the academic domain. Therefore, this paper contributes to the knowledge domain by proposing a novel taxonomy that helps to overcome the lack of connection between academy and industry. The framework helps to navigate among the three different use cases of software, theory and problem-solving to support the communication and collaboration between industry and academia.

In future work, this taxonomy can be further developed and used to identify mutual benefits in the area of PPM or can be applied in other research areas because of its generic nature. This presumption makes the author believe that the framework may also be applicable outside of the PPM area. Additionally, the conducted SLR provides a qualified background to identify research gaps or promote further investigations.

References

1. van der Aalst, W.M.P., Schonenberg, M.H., Song, M.: Time prediction based on process mining. Inf. Syst. 36, 450–475 (2011). https://doi.org/10.1016/j.is.2010.09.001
2. van der Aalst, W.: Process Mining - Data Science in Action. Springer Berlin Heidelberg, Berlin, Heidelberg (2016)
3. van der Aalst, W., Adriansyah, A., de Medeiros, A.K.A., Arcieri, F., Baier, T., Blickle, T., Bose, J.C., van den Brand, P., Brandtjen, R., Buijs, J., Burattin, A., Carmona, J., Castellanos, M., Claes, J., Cook, J., Costantini, N., Curbera, F., Damiani, E., de Leoni, M., Delias, P., van Dongen, B.F., Dumas, M., Dustdar, S., Fahland, D., Ferreira, D.R., Gaaloul, W., van Geffen, F., Goel, S., Günther, C., Guzzo, A., Harmon, P., ter Hofstede, A., Hoogland, J., Ingvaldsen, J.E., Kato, K., Kuhn, R., Kumar, A., La Rosa, M., Maggi, F.M., Malerba, D., Mans, R.S., Manuel, A., McCreesh, M., Mello, P., Mendling, J., Montali, M., Motahari-Nezhad, H.R., zur Muehlen, M., Munoz-Gama, J., Pontieri, L., Ribeiro, J., Rozinat, A., Seguel Pérez, H., Seguel Pérez, R., Sepúlveda, M., Sinur, J., Soffer, P., Song, M., Sperduti, A., Stilo, G., Stoel, C., Swenson, K., Talamo, M., Tan, W., Turner, C., Vanthienen, J., Varvaressos, G., Verbeek, E., Verdonk, M., Vigo, R., Wang, J., Weber, B., Weidlich, M., Weijters, T., Wen, L., Westergaard, M., Wynn, M.: Process Mining Manifesto. In: BPM 2011: Business Process Management Workshops. pp. 169–194 (2012)
4. Alias, C., Rawet, V.L., Neto, H.X.R., Reymão, J. do E.N.: Investigating into the Prevalence of Complex Event Processing and Predictive Analytics in the Transportation and Logistics Sector: Initial Findings From Scientific Literature. In: MCIS 2016 Proceedings. pp. 1–17 (2016)
5. Bevacqua, A., Carnuccio, M., Folino, F., Guarascio, M., Pontieri, L.: A data-adaptive trace abstraction approach to the prediction of business process performances. In: ICEIS 2013 - Proceedings of the 15th International Conference on Enterprise Information Systems. pp. 56–65 (2013)
6. Borkowski, M., Fdhila, W., Nardelli, M., Rinderle-Ma, S., Schulte, S.: Event-based failure prediction in distributed business processes. Inf. Syst. 81, 220–235 (2019).
7. Breuker, D., Matzner, M., Delfmann, P., Becker, J.: Comprehensible Predictive Models for Business Processes. MIS Q. 40, 1009–1034 (2016). https://doi.org/10.25300/misq/2016/40.4.10
8. Castellanos, M., Casati, F., Dayal, U., Shan, M.-C.: A Comprehensive and Automated Approach to Intelligent Business Processes Execution Analysis. Distrib. Parallel Databases. 16, 239–273 (2004). https://doi.org/10.1023/B:DAPD.0000031635.88567.65
9. van Dongen, B.F., Crooy, R.A., van der Aalst, W.M.P.: Cycle Time Prediction: When Will This Case Finally Be Finished? In: OTM 2008: On the Move to Meaningful Internet Systems: OTM 2008. pp. 319–336 (2008)
10. Dumas, M., La Rosa, M., Mendling, J., Reijers, H.A.: Fundamentals of Business Process Management. Springer Berlin Heidelberg, Berlin, Heidelberg (2018)
11. Evermann, J., Rehse, J.-R., Fettke, P.: A Deep Learning Approach for Predicting Process Behaviour at Runtime. In: International Conference on Business Process Management 2016. pp. 327–338 (2017)

12. Evermann, J., Rehse, J.R., Fettke, P.: XES tensorflow - Process prediction using the tensorflow deep-learning framework. CEUR Workshop Proc. 1848, 41–48 (2017)
13. Federici, M., Rizzi, W., Di Francescomarino, C., Dumas, M., Ghidini, C., Maggi, F.M., Teinemaa, I.: A ProM operational support provider for predictive monitoring of business processes. In: CEUR Workshop Proceedings. pp. 1–5 (2015)
14. Di Francescomarino, C., Dumas, M., Federici, M., Ghidini, C., Maggi, F.M., Rizzi, W.: Predictive business process monitoring framework with hyperparameter optimization. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp. 361–376 (2016)
15. Di Francescomarino, C., Dumas, M., Federici, M., Ghidini, C., Maggi, F.M., Rizzi, W., Simonetto, L.: Genetic algorithms for hyperparameter optimization in predictive business process monitoring. Inf. Syst. 74, 67–83 (2018). https://doi.org/10.1016/j.is.2018.01.003
16. Francescomarino, C. Di, Dumas, M., Maggi, F.M., Teinemaa, I.: Clustering-Based Predictive Process Monitoring. IEEE Trans. Serv. Comput. 12, 896–909 (2019).
17. Di Francescomarino, C., Ghidini, C., Maggi, F.M., Milani, F.: Predictive Process Monitoring Methods: Which One Suits Me Best? In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp. 462–479 (2018)
18. Ghattas, J., Soffer, P., Peleg, M.: Improving business process decision making based on past experience. Decis. Support Syst. 59, 93–107 (2014). https://doi.org/10.1016/j.dss.2013.10.009
19. Harzing, A.W.: Publish or Perish
20. Jorbina, K., Rozumnyi, A., Verenich, I., Di Francescomarino, C., Dumas, M., Ghidini, C., Maggi, F.M., La Rosa, M., Raboczi, S.: Nirdizati: A web-based tool for predictive process monitoring. In: CEUR Workshop Proceedings (2017)
21. Kitchenham, B.: Procedures for performing systematic reviews. Keele, UK, Keele Univ. 33. 1–26 (2004)
22. Kofod-petersen, A.: How to do a structured literature review in computer science. Researchgate. 1–7 (2014)
23. Lee, W.L.J., Parra, D., Munoz-Gama, J., Sepúlveda, M.: Predicting process behavior meets factorization machines. Expert Syst. Appl. 112, 87–98 (2018). https://doi.org/10.1016/j.eswa.2018.05.035
24. Leontjeva, A., Conforti, R., Di Francescomarino, C., Dumas, M., Maggi, F.M.: Complex symbolic sequence encodings for predictive monitoring of business processes. Int. Conf. Bus. Process Manag. 2016. 9253, 297–313 (2015). https://doi.org/10.1007/978-3-319-23063-4_21
25. Maggi, F.M., Di Francescomarino, C., Dumas, M., Ghidini, C.: Predictive monitoring of business processes. Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics). 8484 LNCS, 457–472 (2014). https://doi.org/10.1007/978-3-319-07881-6_31
26. Maisenbacher, M., Weidlich, M.: Handling Concept Drift in Predictive Process Monitoring. In: Proceedings - 2017 IEEE 14th International Conference on Services Computing, SCC 2017. pp. 1–8 (2017)
27. Márquez-Chamorro, A.E., Resinas, M., Ruiz-Cortés, A., Toro, M.: Run-time prediction of business process indicators using evolutionary decision rules. Expert Syst. Appl. 87, 1–14 (2017). https://doi.org/10.1016/j.eswa.2017.05.069
28. Marquez-Chamorro, Eduardo, A., Resinas, M., Ruiz-Cortes, A.: Predictive monitoring of business processes: A survey. IEEE Trans. Serv. Comput. 11, 962–977 (2018). https://doi.org/10.1109/TSC.2017.2772256
29. Mehdiyev, N., Evermann, J., Fettke, P.: A multi-stage deep learning approach for business process event prediction. 2017 IEEE 19th Conf. Bus. Informatics. 1, 119–128 (2017). https://doi.org/10.1109/CBI.2017.46
30. Mehdiyev, N., Evermann, J., Fettke, P.: A Novel Business Process Prediction Model Using a Deep Learning Method. Bus. Inf. Syst. Eng. 62, 143–157 (2020). https://doi.org/10.1007/s12599-018-0551-3
31. Metzger, A., Leitner, P., Ivanovic, D., Schmieders, E., Franklin, R., Carro, M., Dustdar, S., Pohl, K.: Comparing and Combining Predictive Business Process Monitoring Techniques. IEEE Trans. Syst. Man, Cybern. Syst. 45, 276–290 (2015). https://doi.org/10.1109/TSMC.2014.2347265
32. zur Mühlen, M., Shapiro, R.: Business Process Analytics. In: Handbook on Business Process Management 2. pp. 137–157. Springer Berlin Heidelberg, Berlin, Heidelberg (2010)
33. Navarin, N., Vincenzi, B., Polato, M., Sperduti, A.: LSTM networks for data-aware remaining time prediction of business process instances. In: 2017 IEEE Symposium Series on Computational Intelligence, SSCI 2017 - Proceedings. pp. 1–7 (2018)

34. Pandey, S., Nepal, S., Chen, S.: A test-bed for the evaluation of business process prediction techniques. 7th Int. Conf. Collab. Comput. Networking, Appl. Work. 382–391 (2011). https://doi.org/10.4108/icst.collaboratecom.2011.247129
35. Polato, M., Sperduti, A., Burattin, A., Leoni, M. de: Time and activity sequence prediction of business process instances. Computing. 100, 1005–1031 (2018).
36. Polato, M., Sperduti, A., Burattin, A., De Leoni, M.: Data-aware remaining time prediction of business process instances. In: Proceedings of the International Joint Conference on Neural Networks. pp. 816–823 (2014)
37. Poll, R., Polyvyanyy, A., Rosemann, M., Röglinger, M., Rupprecht, L.: Process forecasting: Towards proactive business process management. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp. 496–512 (2018)
38. Rogge-Solti, A., Weske, M.: Prediction of Remaining Service Execution Time Using Stochastic Petri Nets with Arbitrary Firing Delays. In: ICSOC 2013: Service-Oriented Computing. pp. 389–403 (2013)
39. Salfner, F., Lenk, M., Malek, M.: A survey of online failure prediction methods. ACM Comput. Surv. 42, 1–42 (2010). https://doi.org/10.1145/1670679.1670680
40. Schmidt, W.: Business Activity Monitoring (BAM). In: Rausch, P., Sheta, A.F., and Ayesh, A. (eds.) Business Intelligence and Performance Management. pp. 229–242. Springer London, London (2013)
41. Senderovich, A., Di Francescomarino, C., Ghidini, C., Jorbina, K., Maggi, F.M.: Intra and inter-case features in predictive process monitoring: A tale of two dimensions. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp. 306–323 (2017)
42. Senderovich, A., Weidlich, M., Gal, A., Mandelbaum, A.: Queue mining for delay prediction in multi-class service processes. Inf. Syst. 53, 278–295 (2015).
43. van der Spoel, S., van Keulen, M., Amrit, C.: Process Prediction in Noisy Data Sets: A Case Study in a Dutch Hospital. In: International Symposium on Data-Driven Process Discovery and Analysis. pp. 60–83 (2013)
44. Tax, N., Teinemaa, I., van Zelst, S.J.: An interdisciplinary comparison of sequence modeling methods for next-element prediction. Softw. Syst. Model. (2020). https://doi.org/10.1007/s10270-020-00789-3
45. Tax, N., Verenich, I., La Rosa, M., Dumas, M.: Predictive business process monitoring with LSTM neural networks. In: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). pp. 477–492 (2017)
46. Teinemaa, I., Dumas, M., Leontjeva, A., Maggi, F.M.: Temporal stability in predictive process monitoring. Data Min. Knowl. Discov. 32, 1306–1338 (2018). https://doi.org/10.1007/s10618-018-0575-9
47. Teinemaa, I., Dumas, M., Maggi, F.M., Di Francescomarino, C.: Predictive Business Process Monitoring with Structured and Unstructured Data. In: BPM 2016: Business Process Management. pp. 401–417 (2016)
48. Teinemaa, I., Dumas, M., Rosa, M. La, Maggi, F.M.: Outcome-oriented predictive process monitoring: Review and benchmark. ACM Trans. Knowl. Discov. Data. 13, (2019). https://doi.org/10.1145/3301300
49. Tu, T.B.H., Song, M.: Analysis and Prediction Cost of Manufacturing Process Based on Process Mining. In: 2016 International Conference on Industrial Engineering, Management Science and Application (ICIMSA). pp. 1–5. IEEE (2016)
50. Verenich, I.: A general framework for predictive business process monitoring. (2016)
51. Verenich, I., Dumas, M., La Rosa, M., Maggi, F.M., Di Francescomarino, C.: Complex symbolic sequence clustering and multiple classifiers for predictive process monitoring. In: International Conference on Business Process Management 2016. pp. 218–229 (2016)
52. Verenich, I., Dumas, M., La Rosa, M., Maggi, F.M., Di Francescomarino, C.: Minimizing overprocessing waste in business processes via predictive activity ordering. Int. Conf. Adv. Inf. Syst. Eng. 9694, 186–202 (2016). https://doi.org/10.1007/978-3-319-39696-5_12
53. Verenich, I., Dumas, M., Rosa, M. La, Maggi, F.M., Teinemaa, I.: Survey and Cross-benchmark Comparison of Remaining Time Prediction Methods in Business Process Monitoring. ACM Trans. Intell. Syst. Technol. 10, 1–34 (2019). https://doi.org/10.1145/3331449
54. Verenich, I., Nguyen, H., Rosa, M. La, Dumas, M.: White-box prediction of process performance indicators via flow analysis. ACM Int. Conf. Proceeding Ser. Part F1287, 85–94 (2017).