Recommender Systems in Business Process Management: A Systematic Literature Review

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Abstract: Recommender systems have the potential to enhance decision-making and to improve business process execution in the domain of Business Process Management (BPM). By analyzing data and providing personalized recommendations, these systems can assist users in making profound decisions and so foster the achievement of their business goals. In our study that is based on the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) methodology, we examine the usage of recommender systems in BPM, focusing on the objectives, methods, and input data utilized. We searched eight databases and included papers that focus on process execution and recommendation methods while excluding those that are not digitally available, not in English, patents, miscellany, or proceedings, or focused solely on business process modeling. This results in 33 papers, addressing the research questions, that are analysed in detail. The discussion highlights research gaps related to user preferences and input data, suggesting that further investigation is needed to enhance the effectiveness of recommender systems in business process management.

1 INTRODUCTION

The core elements of Business Process Management (BPM) are processes that reflect sequences of working steps having to be executed in a specific order (Dumas et al., 2018; Weske, 2007). For process modelling process models in a business process modelling language are defined. Each working step is represented by an activity within a process model. Furthermore, control flow (i.e., the order of the activities), data used, and resources eligible to execute the activities are specified in the process model. Process-aware Information Systems (PAISs) interpret process models and execute them (Reichert and Weber, 2012). A PAIS determines which activities to be performed next can be executed next by what process participant. Tasks ready for execution are provided to the process participants in so-called worklists. Once a task is completed, information about its execution is stored in a process event log (van der Aalst, W, 2016). A process event comprises information about the task itself, the resource, i.e. process participant, executed the task, and further details like date, duration, and optional customer data. Events belonging to the execution of a specific instance of a business process constitute a so-called (event) trace.

Since all kinds of enterprises rely on BPM process improvement is a major success factor for them. Various approaches for process improvement have been developed. Typically, they aim to optimize a business process execution in respect of certain goals. Respective goals are reduction of process cycle time, improvement of process outcomes, or increase of user satisfaction (Jablonski and Bussler, 1996; Koulopolous, 1995; Lawrence, 1997; Petter et al., 2022). It is common practice to deploy recommendations in PAISs that support process participants to better achieve those goals.

Recommender systems are mainly known from e-commerce. A recommender system is a software system that provides personalized recommendations to users (Aggarwal, 2016). They have become increasingly popular in e-commerce due to their potential to increase customer engagement and sales and to improve customer experience. Three main methods have been developed to generate recommendations: *collaborative filtering*, *content-based filtering*, and *knowledge-based filtering*. Collaborative filtering relies on users' past explicit (e.g., issuing "stars") and implicit (e.g. chosen actions) ratings and based on that constitutes classes of users with similar preferences. Personalized recommendations are then de-

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rived from the behavior of an associated user class. In content-based filtering attributes of things (e.g. activities) a user likes are referred to as ”content”. A recommender system recommends similar things to user, i.e. things that coincide in all/most of the content attributes. Knowledge-based filtering uses a user profile and evaluates whether a particular item is likely to be of interest to a user, again based on the contextual attributes of items. Furthermore, these three methods can mutually be combined, forming what is known as hybrid filtering.

Over time, different methods of recommender systems have been integrated into BPM. These methods vary concerning - among others - the objectives they are aiming at, the input data they are exploiting, and the algorithms they install. In some cases, different methods aim at achieving the same objective but in different ways.

Currently, there are two systematic literature reviews regarding recommendations in BPM (Kubrak et al., 2021; Yari Eili and Rezaeenour, 2022). Kubrak et al. consider the recommendation of interventions at runtime to prevent negative outcomes or poorly performing cases. That means, this review focuses on predictive process monitoring. They provide an overview of recent research papers regarding performance objectives with a focus on control flow, resource allocation, and other perspectives (Kubrak et al., 2021). In a second literature review, Yari Eili and Jalal Rezaeenour focus on the usage of event logs as source for recommendations. These approaches rely on process mining techniques to exploit event log information. The authors discuss different types of recommendations and evaluation metrics applied in the considered research papers (Yari Eili and Rezaeenour, 2022).

We broaden the perspective of a systematic literature review compared with the above introduced predecessor reviews. We neither restrict ourselves to predictive process monitoring as objective, nor do we exclusively focus on event logs as information resource. To the best of our knowledge, we present a first systematic literature review on the application of recommender systems in the realm of BPM without any restrictions. To address this we focus on the following research questions:

RQ_1. What is the objective of applying recommendation methods, respectively recommender systems, in the context of BPM?

RQ_2. What data provided by a PAIS is used to generate recommendations?

RQ_3. Which methods known from RS are applied?

RQ_1 focuses on the objectives the approaches foster applying RS during process execution. Many research papers focus on optimizing process performance (e.g., shortening processing time, increasing quality), whereas few papers consider other goals like improving user satisfaction (Petter et al., 2022). RQ_2 and RQ_3 consider the methods used to generate recommendations and the input input data they require. For example, the trace of a currently executed process instance can be used, as well as the complete event log provided so far by the PAIS.

To answer the above research questions, we conduct a systematic literature review following the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) method (Page et al., 2021) as far as applicable. After establishing the research questions, the search strategy to identify research papers is defined, including all accessed databases and applied search queries. Furthermore, inclusion and exclusion criteria are defined to qualify the results of such queries. Extracting data from the found records leads to a detailed analysis of the remaining records. The last step is the interpretation of the papers according to the research questions.

The remainder of the paper is structured as follows: Section 2 gives a detailed overview of the methods used to identify relevant research papers. The step-wise execution of the literature review and the obtained results are presented in Section 3. Section 4 provides a discussion of the results, and finally, Section 5 concludes the systematic literature review and highlights essential directions for future research.

2 METHODS

This paper describes a systematic literature review conducted according to PRISMA guidelines (Page et al., 2021) to identify and analyse existing research integrating recommender systems into BPM systems. More specifically, we investigate why recommender systems are used in the context of BPM (RQ_1), what data is used (RQ_2), and which methods known from genuine recommender systems come into use (RQ_3). The PRISMA method includes guidance on planning, conducting, reporting, and disseminating systematic reviews and meta-analyses transparently. It involves formulating an appropriate research question, performing comprehensive searches, selecting studies that meet predefined inclusion criteria, extracting relevant data from each study, synthesizing results, and interpreting results critically with respect to limitations of included studies and the quality of evidence provided by them. This process allows researchers to draw reliable conclusions about existing

Table 1: The search queries applied.

ID	Search Query
Q1	"*Recommender System*" AND "*Business Process Management*"
Q2	"*Recommender Systems*" AND "*Business Process Management*"
Q3	"*Recommendation System*" AND "*Business Process Management*"
Q4	"*Recommendation Systems*" AND "*Business Process Management*"

evidence on any given topic while minimizing bias in the review process.

According to the PRISMA checklist, first, we define the databases to access. A total of eight different data sources are searched to find as many relevant research as possible: ACM Digital Library, Emerald, Google Scholar, IEEE Explore, ScienceDirect, Scopus, SpringerLink, and Web Of Science. We apply the software *Publish or Perish* (Harzing, 2007) for the search with Google Scholar and Scopus. Since Google Scholar limits the number of results for each query to at most 1000 results, we split the query into multiple queries according to different periods and unified them afterward. The queries posted are shown in table 1. Notice that we post four separated queries for every database instead of connecting the keywords by the logical operator *OR* since some databases cannot handle this operator properly. Furthermore, a distinction is made between *Recommender System* and *Recommender Systems*, respectively *Recommendation System* and *Recommendation Systems*, as many databases provide different results due to the plural form of the terms.

Second, eligibility criteria (e.g., inclusion and exclusion criteria) must be defined. In our literature review, we address the objectives of the considered literature, the data used, and the methods applied. From this basis, two inclusion criteria are derived:

IC_1. Process execution

IC_2. Recommendation methods (content-based filtering, collaborative filtering, knowledge-based filtering, hybrid filtering)

Inclusion criterion IC_1 requires that papers considering process execution must be included. Also, all papers that explicitly apply certain methods from the domain of recommender systems to the domain of BPM must be taken into account (IC_2).

Furthermore, the following exclusion criteria are defined to exclude papers from the evaluation:

EC_1. Not digitally available

EC_2. Not written in English

EC_3. Patents, miscellany, and proceedings

EC_4. Only one domain is considered: BPM or RS

EC_5. Business process modeling optimization

Exclusion criteria EC_1 and EC_2 ensure that papers are generally available and are written in English, so they can be accessed by the majority of researchers. EC_3 says that patents, miscellany, and proceedings "as a whole" are excluded. Nevertheless this does not exclude the contents of these sources. For example, papers of a proceeding are included as long as they fulfill the inclusion and exclusion criteria. Exclusion criterion IC_4 stipulates that both domains must be considered, BPM and recommendation systems. This criterion excludes papers that only cover one of the two domains. Finally, EC_5 excludes those papers that solely focus on optimization of process modeling without looking at process execution.

In summary, the inclusion criteria IC_1 and IC_2 provide the basis for our systematic literature analysis, while the exclusion criteria EC_1 to EC_5 help to narrow down the scope and focus of the study.

After having defined search strategy and inclusion and exclusion criteria (eligibility criteria), respectively, we define our selection process. We first capture the metadata of a publication (title, author, publication venue, year, keywords, year, DOI). Based on the metadata, duplicate entries are removed semi-automatically (tool support from Microsoft Excel (Microsoft Corporation, 2022)). In order to consider a found record in future steps, the record must not violate the exclusion criteria. To ensure this, all authors of this study check the title of each record independently. The resulting records are checked according to their abstract afterwards, again independently by each author of this paper. The records left are entirely read by the authors. Depending on the content, they are excluded because they violate one or more exclusion criteria, or they are sorted into a table and classified according to their objectives, data used, and methods applied. To identify even more relevant research, we conduct backward referencing (snowballing) to the papers found (Okoli and Schabram, 2010).

3 RESULTS

3.1 Applying the PRISMA Method

To get an overview of the existing research combining recommender systems and BPM, we applied the PRISMA method described in Section 2. This method comprises a flow diagram (Page et al., 2021) that provides a visual representation of the search process and the number of studies included or excluded at each stage. It offers a rigorous and transparent view on the literature finding and selecting process and clearly illustrates the results of the systematic review. The adapted PRISMA flow diagram for our study is shown in Figure 1.

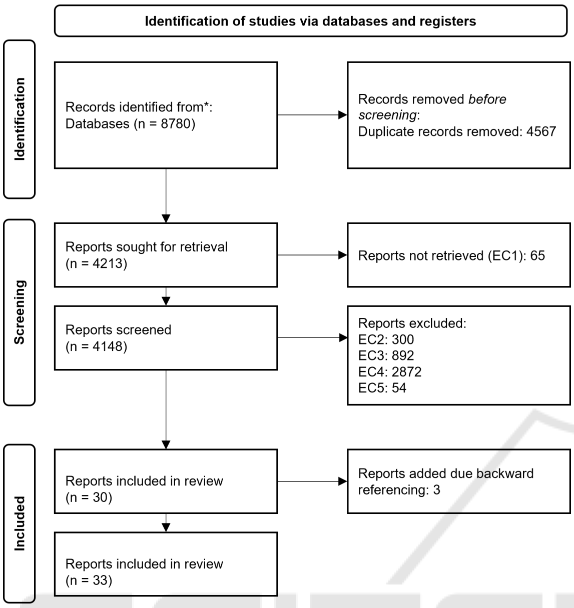

Figure 1: PRISMA flow diagram of our study.

Identification. The search process is initiated by searching eight different databases: ACM, Emerald, Google Scholar, IEEE Xplore, Science Direct, Scopus, Springer, and WebOfScience. For each database we run the four queries introduced in Table 1. On January 10th, 2023 we conducted our search and identified a total of 8780 records. Table 2 depicts detailed results of the query execution. The columns represent the search queries, the rows identify the different databases considered. Each cell shows the results of query execution for the particular databases. Notice that the number of entries found for *Recommender System* and *Recommender Systems*, respectively, and for *Recommendation System* and *Recommendation Systems*, respectively, is the same for the databases Emerald, IEEE Xplore, Science Direct, and Scopus, whereas in the remaining databases different numbers of entries are found for the singular and plural forms of these terms. This highlights the importance of applying a consistent and standardized search strategy, as different databases may have different ways of indexing and categorizing literature. According to the PRISMA method in the next step the 8780 papers have to be screened for duplicate entries. 4567 of these records are identified as duplicates and are therefore excluded, leaving 4213 unique records.

Screening. Out of these, 65 are not available in digital form and are also excluded from the study (EC_1). The remaining 4148 papers are subject to further screening. Another 300 papers are excluded since they are not written in English (EC_2). 892 additional entries are excluded because they are either patents, miscellanies, or proceedings (EC_3). 2872 papers are excluded as they either do not consider both, BPM and recommender systems, or have an inadequate focus on these topics (EC_4). Finally, 54 papers are excluded as they focus on recommender systems in the context of process modeling, which is also outside the scope of the present study (EC_5). This results in 30 papers that are included in our study.
Included. A total of 3 papers are added through backward referencing, resulting in a final list of 33 papers to be analyzed in this research.

3.2 Classification of the Result

For a better overview of the 33 papers we have analyzed and classified them as depicted in Table 3. We identified three superior columns referring to the research questions defined in Section 1: *Objectives* (RQ_1), *Input Data* (RQ_2), and *Methodology* (RQ_3). Each row of the table represents a study or a paper to be analyzed.
Objectives. The *Objectives* column lists the most frequently mentioned objectives that the reviewed papers are aiming at when applying recommender systems in the BPM context. Process performance goals, such as shortening processing time and minimizing costs, are the most frequently mentioned goals. Additionally, the papers consider flexible goals that can be customized based on a target function provided. For example, a flexible goal may aim at the optimization of different KPIs, such as process completion time, resource utilization, and customer satisfaction. Often, process performance goals and flexible goals overlap. Enhancing user experience and user satisfaction is one of the original goals of recommender systems. This goal is still relevant in the field of Business Process Management and is pursued by researchers. The column *Others* summarizes goals that do not fit into the above categories. For example, a paper may aim at the reduction of process errors.
Input Data. The *Input Data* column of the table lists the different types of data exploited by the reviewed papers as input for recommendations. The data listed in this column can be divided into six sub-areas: Event log, partial traces, worklist, resource information, process model, and others. Many approaches require the event log, which records the events that occur in a business process, to generate recommen-

Table 2: Published articles in journals and conferences.

	Q_1	Q_2	Q_3	Q_4	Sum
ACM DL	16	37	18	23	94
Emerald	54	54	48	48	204
Google Scholar	961	1442	1293	792	4488
IEEE XPlore	199	199	576	576	1550
ScienceDirect	81	81	62	62	286
Scopus	24	24	15	15	78
SpringerLink	547	563	474	469	2053
Web Of Science	8	7	6	6	27
Sum	1890	2407	2492	1991	8780

dations. The event log can be extended to include additional information such as process attributes or resource preferences (Petter et al., 2022). Additionally, partial traces (e.g., sequences of events) can be used to generate recommendations based on the history of events in a process. A worklist contains information about the tasks that must be performed in a business process. Recommendations can be generated based on the information contained in such a worklist. Furthermore, resource information, such as the availability of a resource, is often necessary to generate adequate recommendations. A process model (containing information about the activities that need to be performed) and additional attributes, such as contextual information for activities, are used in some reviewed papers to make recommendations. For instance, recommendations are derived that are based on the similarity of these task attributes. Any other input data that does not fit into the previously mentioned categories is grouped under *Others*. The use of different types of input data can significantly influence the accuracy and efficiency of the recommendations. Furthermore, the methodology used to calculate recommendations is depending on the input data provided.

Methodology. The *Methodology* column of the table categorizes the different methods applied in the reviewed papers for recommendations in the field of BPM. Content-based filtering uses the attributes of the items being recommended (e.g., tasks in a business process) and the execution history of the user considered to generate recommendations. A collaborative filtering method generates recommendations based on users' past behavior and preferences. It assumes that users who have similar preferences in the past will have similar preferences in the future. Knowledge-based filtering is based on knowledge representation and reasoning to generate recommendations. It can take into account various factors, such as user profiles. As the name suggests, hybrid filtering combines the advantages of multiple filtering methods to generate recommendations. For example, a hybrid method uses content-based filtering to generate initial recommendations and then refine these recommendations using collaborative filtering. In addition to these standard methods, the column *Others* accommodates all papers that do not fit into the previously mentioned categories.

3.3 Presentation of the Classified Results

In the following section the results are discussed regarding their objectives. In this study, the authors analyzed a total of 15 papers with the aim of optimizing process performance goals. Out of the analyzed papers, 100% aim at shortening processing time, 40% aim at minimizing costs, and 33% aim at improving the quality of process outcome. Furthermore, 13 papers consider flexible optimization goals, four papers regard user preferences as optimization goal, and 14 papers are assigned to the column of "other" objectives.

Shorten Processing Time. The majority of the papers focuses on the optimization of process performance goals by shortening processing time (15 papers). This list comprises (Arias et al., 2016), (Schobel and Reichert, 2017), (van der Aalst et al., 2010), (van der Aalst et al., 2010), (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), (Agarwal et al., 2022), (Branchi et al., 2022), (Huber et al., 2015), (Weinzierl et al., 2020), (Bozorgi et al., 2021), (Schonenberg et al., 2008), (Barba et al., 2012), (Barba et al., 2013), (Aalst et al., 2009), and (Haisjackl and Weber, 2011). These papers analyse an event log to extract the potential process execution time. Some papers, such as (Barba et al., 2012) and (Barba et al., 2013), use the event log to derive information about contextual information like execution times for the single activities in a process model. Enacting the model with such information during build time leads to simple generation of recommendations during runtime. During process execution, the trace with the shortest remaining processing time can be recom-

Table 3: Overview of the analyzed research papers.

Research Paper	**Objectives**						**Input Data**						**Methodology**				
	Shorten processing time	Minimize costs / Increase profit	Quality	Flexible goal	User experience	Others	(Enhanced) Event log	Partial traces	Worklist	Resource Information	Process model	Others	Content-based filtering	Collaborative filtering	Knowledge-based filtering	Hybrid filtering	Others
(Yang et al., 2017)				•			•	•									•
(Arias et al., 2016)	•	•		•		•	•	•		•							•
(Pika and Wynn, 2021)						•	•										•
(Arias et al., 2017)					•		•			•			•				
(Schobel and Reichert, 2017)	•					•	•	•									•
(Conforti et al., 2015)						•	•					•	•				
(Zhao et al., 2016)						•	•	•						•			
(van der Aalst et al., 2010)	•						•	•									•
(Petter et al., 2022)					•		•		•			•	•				
(Di Valentin et al., 2014)					•					•		•			•		
(Khan et al., 2021)				•			•		•								•
(Leoni et al., 2020)				•			•	•					•				
(Setiawan and Sadiq, 2011)	•	•	•	•		•	•	•	•					•			
(Setiawan et al., 2011)	•	•	•	•		•	•	•	•					•			
(Mertens et al., 2015)						•		•			•						•
(Agarwal et al., 2022)	•		•	•			•	•	•								•
(Arias et al., 2018)						•	•		•			•	•				
(Branchi et al., 2022)	•	•		•			•	•						•			
(Huber et al., 2015)	•						•	•									•
(Liu and Wu, 2018)				•			•					•				•	
(Bidar et al., 2019)					•		•		•				•				
(Gröger et al., 2014)						•	•	•									•
(Weinzierl et al., 2020)	•			•			•	•			•						•
(Bozorgi et al., 2021)	•						•	•									•
(Arias et al., 2016)						•	•			•			•				
(Schonenberg et al., 2008)	•		•	•			•	•	•								•
(Barba et al., 2012)	•						•	•		•	•	•			•		
(Trabelsi et al., 2021)						•					•	•					•
(Barba et al., 2013)	•						•	•		•	•	•			•		
(Pika and Wynn, 2020)						•	•							•			
(Aalst et al., 2009)	•	•		•			•	•									•
(Cabanillas et al., 2013)						•	•		•	•		•					•
(Haisjackl and Weber, 2011)	•	•	•	•			•	•	•								•

mended. The remaining 13 papers are calculating recommendations by deriving the potential process execution time by comparing the current partial trace with similar traces in the event log. In addition to the event log and the partial trace, some papers consider contextual information such as user expertise (Arias et al., 2016; Setiawan and Sadiq, 2011; Setiawan et al., 2011), resource availability (Arias et al., 2016; Barba et al., 2012; Barba et al., 2013), and explicit domain knowledge (Aalst et al., 2009) to optimize the process execution time. None of the papers regarding shortening processing time can be assigned to the methodology of content-based filtering or hybrid filtering. The method of collaborative filtering is used in (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), and (Branchi et al., 2022), where the executed events of the current user are compared to the executed events of other users. Knowledge-based filtering can be found in (Barba et al., 2012) and (Barba et al., 2013). Both papers enhance the process model with contextual information providing recommendations during runtime. The remaining papers in the section apply methods that cannot be assigned to the standard methods known from recommender systems since they are not user-specific.

Flexible Goals. Flexible goals that can be defined during build- or run-time have become increasingly important for many organizations due to the changing nature of business requirements and goals. To achieve these flexible goals, different techniques and approaches have been proposed and investigated in the literature. In this study, we review 13 papers that consider flexible goals in their research and provide a summary of the techniques and methods used: (Yang et al., 2017), (Arias et al., 2016), (Khan et al., 2021), (Leoni et al., 2020), (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), (Agarwal et al., 2022), (Branchi et al., 2022), (Liu and Wu, 2018), (Weinzierl et al., 2020), (Schonenberg et al., 2008), and (Haisjackl and Weber, 2011). Most of the papers reviewed use Key Performance Indicators (KPIs) to define their objectives. These KPIs are metrics that are used to measure the performance of a process, system, or organization. For instance, minimizing costs (Agarwal et al., 2022; Branchi et al., 2022), shortening processing time (Agarwal et al., 2022; Branchi et al., 2022; Weinzierl et al., 2020), and increasing customer satisfaction (Setiawan and Sadiq, 2011) are some of the common KPIs used to define objectives in the reviewed papers. However, in (Schonenberg et al., 2008), the objective is defined via a target function. To calculate recommendations for achieving the objectives, all papers use event log information. Some of the papers use an enhanced event log that includes additional information, such as customer satisfaction, to generate more accurate recommendations. For example, (Leoni et al., 2020), include customer satisfaction information in their enhanced event log to generate recommendations that can improve customer satisfaction. Partial traces are used by 70% of the papers to generate recommendations (Yang et al., 2017; Arias et al., 2016; Leoni et al., 2020; Setiawan and Sadiq, 2011; Setiawan et al., 2011; Agarwal et al., 2022; Branchi et al., 2022; Weinzierl et al., 2020; Schonenberg et al., 2008; Aalst et al., 2009; Haisjackl and Weber, 2011). By analyzing partial traces, recommendations can be generated that can help achieve the objectives defined in the KPIs. Worklists of current users are also used in some papers to generate recommendations (Khan et al., 2021; Setiawan and Sadiq, 2011; Setiawan et al., 2011; Agarwal et al., 2022; Schonenberg et al., 2008; Haisjackl and Weber, 2011). Since worklists contain information about the tasks, a user can potentially work on, this information can be used to generate recommendations that can help the user achieve their objectives. Less frequently considered input data for generating recommendations during process execution are business data (Liu and Wu, 2018), domain knowledge (Aalst et al., 2009), and resource information (Setiawan and Sadiq, 2011; Setiawan et al., 2011). For example, (Aalst et al., 2009) use domain knowledge to generate recommendations that can improve the quality of a process. Collaborative filtering is a method used by some of the papers to generate recommendations. Collaborative filtering is a technique that is commonly used in recommender systems to provide recommendations to users based on the behavior of similar users. In the context of flexible goals, collaborative filtering can be used to provide recommendations to users based on the behavior of other users who have similar objectives. For instance, (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), and (Branchi et al., 2022) use collaborative filtering to generate recommendations. Finally, some of the papers use methods that cannot be assigned to the standard methods known from recommender systems.

Minimizing Costs. The objective of minimizing costs during process execution is in the focus of six research papers, namely (Arias et al., 2016), (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), (Branchi et al., 2022), and (Aalst et al., 2009). The common approach adopted by these papers is to use event logs and partial traces to generate recommendations. While some of the papers consider the current worklist of the user such as (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), and (Haisjackl and Weber, 2011), others like (Yang et al., 2017) incorporate information about resources to calculate recommendations. It is worth noting that the methods used by these papers cannot be directly mapped to the existing methods known from recommender systems. Only three papers, namely (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), and (Branchi et al., 2022), can be classified under the collaborative filtering method.

Quality. The key research area of (Setiawan and Sadiq, 2011), (Setiawan et al., 2011), (Agarwal et al., 2022), (Schonenberg et al., 2008), and (Haisjackl and Weber, 2011) is to improve the quality of the process outcome. The authors of these research papers analyse event logs and partial traces to generate recommendations, while also making use of the current user's worklist. (Setiawan and Sadiq, 2011) and (Setiawan et al., 2011) deploy methods of collaborative filtering to improve process outcomes, applying this technique to event logs and partial traces to develop recommendations for process improvement. On the other hand, the other papers utilize non-standard recommendation methods to achieve their objectives. These papers suggest that there are several methods that can be used to generate recommendations for process improvement, and that different methods may be more efficient in different contexts.

User Experience. The original goal of recommender systems is to provide personalized recommendations to users based on their preferences, behaviors, and context information. In this study, we review four recent studies that focus on improving user experience in BPM through recommender systems: (Arias et al., 2017), (Petter et al., 2022), (Di Valentin et al., 2014), and (Bidar et al., 2019). These studies differ in their focus, methodology, and application domain, but they all share the common goal of enhancing user experience through personalized recommendations. The research papers (Arias et al., 2017), (Petter et al., 2022), and (Bidar et al., 2019) interpret event logs to generate recommendations for users. Event logs are used to infer user preferences and behavior patterns. (Petter et al., 2022) enhances the event log with explicit user preferences which are collected through surveys or questionnaires. This approach allows for a more accurate representation of user preferences and leads to better recommendations. (Arias et al., 2017), (Petter et al., 2022), and (Bidar et al., 2019) consider additional information beyond the event log to improve recommendations. (Arias et al., 2017) incorporates resource information, such as availability and cost, to filter out irrelevant recommendations. (Petter et al., 2022) and (Bidar et al., 2019) analyse the worklist of a current user, which contains tasks that the user can execute, to generate recommendations that are aligned with the user's goals and priorities. In addition to these approaches (Petter et al., 2022) examines additional attributes of activities to calculate similar activities. This approach allows for more fine-grained recommendations that take into account the specific characteristics of different activities, such as their duration, location, or complexity. (Bidar et al., 2019) also extracts implicit user preferences from the event log, such as the frequency or actuality of certain actions, to recommend activities that are more likely to be of interest to the user. The fourth study reviewed, (Di Valentin et al., 2014), focuses on supporting employees in carrying out business processes under the consideration of their personal profile and context information. This study deploys a knowledge-based filtering approach, which involves the use of domain knowledge to make recommendations. Specifically, the study considers the employee's role, skills, and context information to generate personalized recommendations.

Other. Objectives, summarized in the column *Others* are considered in the following. One of the considered objectives during process execution is the allocation of work teams. (Arias et al., 2017) propose a content-based filtering approach to dynamically allocate work teams based on historical process execution data and expertise information. Another important objective is to maximize flexibility. (Mertens et al., 2015) propose a technique that allows the user to retain maximum flexibility by considering partial traces and a declarative process model. This technique enables users to divert from recommendations later on and to perform tasks in their own preferred way. (Arias et al., 2018) and (Arias et al., 2016) propose techniques to recommend the best fitting resource for a task. In (Arias et al., 2018), the authors use contextual information, historical information, and weights to calculate recommendations using content-based filtering methods. In (Arias et al., 2016), the authors use resource information (e.g., expertise) and historical information about past process executions to make recommendations. These approaches can help organizations to allocate resources more effectively and reduce operational costs. Finally, another important objective during process execution is to reduce the risk of process failure. (Conforti et al., 2015) and (Gröger et al., 2014) propose techniques to avoid predicted metric deviation, such as a process running out of time. The goal is achieved by comparing running process instances with historical process data and recommending next best actions according to the results. These approaches can help organizations to avoid process failure and improve their overall efficiency.

4 DISCUSSION

The integration of recommender systems in the context of BPM has gained significant interest in recent years due to its potential to optimize process performance goals. In the context of BPM, these systems can be used to improve process performance by suggesting the best possible next steps for the process. This literature review provides an overview of existing approaches using recommender systems in the context of BPM. The overview unveils several gaps and associated implications for future research.

The main objective of the reviewed studies is to optimize process performance goals using recommender systems. The primary focus is on shortening processing time; however, other performance objectives are represented in only a few examples. The use of various methods and techniques highlights the diversity of research in this area and the potential for new and innovative approaches to be developed. While there is still much work to be done, the research conducted recently provides a strong foundation for further exploration and development in this exciting field. The results from this study suggest that using event logs and partial traces can effectively optimize process execution regarding different goals. While the methods used by most papers cannot be directly mapped to existing methods known from recommender systems, content-based filtering is the most widely used approach for the remaining papers. We observe that the majority of previous studies use the event log to calculate recommendations. According to the domain of recommender systems, depending on historical information is not good at all since often there is no historical information available (cold-start problem).

The review highlights several gaps in the current literature. First, there needs to be more common terminology for using recommender systems in BPM research. Second, the majority of methods in the field aim to improve processes along the temporal perspective (e.g., cycle time, processing time, deadline violations); other performance dimensions are represented in only a few examples. Thus, another research direction is to investigate other performance objectives that could be enhanced via recommender systems. Third, recommender systems are essential for businesses that aim to improve the user experience. The primary goal of these systems is to provide personalized recommendations to users by analyzing their past behavior, preferences, and interests. However, the use of recommender systems in BPM is currently limited, and there is significant space for one of the critical challenges yet to be considered is recommending the next best actions according to the user preferences. To achieve this, there is a need for explicit feedback from users and the use of this feedback to generate recommendations. According to this feedback, content-based and collaborative filtering methods might be used to generate recommendations to improve user experience during process execution. Another possibility is using knowledge-based filtering regarding user-profiles and contextual information for the business process.

In the following paragraph, we will address and provide answers to the research questions. Answering RQ_1, we found that most research papers consider process performance goals as main objectives followed by flexible goals, improving process quality, and improving user experience. The input data the most analyzed papers use to generate recommendations (RQ_2) are event logs next to partial traces. Furthermore, the worklist of the current user, resource information, and the process model are considered. The methods known from recommender systems are hardly considered to generate recommendations in the context of business process management (RQ_3). Hybrid filtering is used by only one paper whereas content-based filtering and collaborative filtering methods are used in seven, respectively, five papers. Most papers calculate recommendations using other methods.

Overall, these studies demonstrate the importance of developing personalized recommender systems that can take into account a wide range of factors, such as user preferences, behavior patterns, context information, and domain knowledge. While the approaches and methodologies used in these studies vary, they all share the goal of enhancing user support and providing relevant, useful, and engaging recommendations. As the use of recommender systems continues to grow in various applications, researchers and practitioners must continue exploring new approaches and methods for developing effective recommender systems that can meet the evolving needs of different users and applications.

Systematic literature reviews have several typical pitfalls and threads to validity (Ampatzoglou et al., 2019; Kitchenham and Charters, 2007). One potential threat is missing relevant publications during the search. This risk is mitigated by conducting a two-phase search that includes a broad range of key terms as well as backward referencing. Another potential threat is to exclude relevant publications during screening. This threat is mitigated by using explicitly defined inclusion and exclusion criteria. Additionally, all unclear cases are examined and discussed by all authors of this paper. A potential bias is subjectivity in applying the inclusion and exclusion criteria to determine the subsumed studies and possible inaccuracies in data analysis. To mitigate these threats, each article is independently assessed against the inclusion and exclusion criteria by all authors. To provide validity, all articles are thoroughly reviewed by two authors.

5 CONCLUSION

In this paper, we present a systematic literature review of recommender systems deployed in the context of BPM. The paper categorizes the research based on the objectives, methodology, and input data. The first goal of the paper is to provide a comprehensive review of the existing literature on the use of recommender systems in the context of BPM. The paper identifies the research conducted in the past, categorizes the research, and analyzes the findings. The second goal is to identify the research gaps in the field of recommender systems in BPM.

The first gap is the need for more detailed consideration of user preferences in the process execution phase. Most of the studies focus on process improvement, ignoring the preferences and experiences of the users. This gap presents an opportunity for future research to explore the use of recommender systems to personalize the process execution for individual users. The second gap is the reliance on event logs as input data. While event logs provide a rich source of data for analyzing the process, they suffer from the cold-start problem. This problem arises when a new process or employee is introduced, and no data is available to train the recommender system. Future research can explore the use of other types of input data, such as process models and user preferences, to overcome this problem.

Finally, this paper is limited to process execution and does not consider other research fields like using recommender systems in the context of business process modeling. To the best of our knowledge, several recommender systems have been proposed to assist process designers in modeling business processes. However, these approaches are not examined in this study.

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