A Conceptual Framework for Resource Analysis in Process Mining

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Abstract. Resource analysis is an emerging branch in process mining that aims to understand behavioral and structural aspects of resources in business processes. A problem of current resource analysis is its fragmentation. The spectrum of corresponding process mining techniques is diverse but scattered, with contributions often focusing on one or the other specific aspects. An overarching framework that could organize resource analysis, tie it to theoretical foundations, and, in turn, inform the development of new analytical methods is missing. In this work, we address this research problem by conducting a systematic literature review to organize the scattered landscape of the state-of-the-art resource analysis methods in process mining. Our work is guided by the question of what resource-related organizational and behavioral patterns can be analyzed with current methods. We classify the methods according to two aspects: what type of phenomenon was analyzed and what design principles were utilized in the development. Our findings highlight that most resource analysis methods in process mining are data-driven, developed to solve a specific business problem, or loosely based on resource analysis concepts from other disciplines. Some good examples of techniques defined for theoretical questions give directions for future research.

Keywords: Process mining · Resource analysis · Systematic literature review.

1 Introduction

The effective management of resources is a key concern of Business Process Management (BPM) [23]. Organizations rely on a multitude of business processes to deliver products and services to their customers. Activities within a business process are performed by various resources, such as human labor, machinery, and software services [13]. Given that these resources are valuable, often expensive, and limited in availability [6], optimizing their occupation is essential for the success and efficiency of business processes. With the growing availability of process execution data, behavioral and structural aspects of resources in business processes [2] can be analyzed with the help of *process mining* techniques. Process mining is a family of techniques that rely on a so-called *event log*, including structurally the events that happen in the execution of a business process, and help to shed transparency into the real-world process enactment. Compared to traditional methods in resource analysis such as labor-intensive and time-consuming interviews and observations, process mining techniques have proven effective for studying resources based on event data [23].

The portfolio of resource analysis methods has expanded in recent years with a diverse spectrum of techniques being proposed [13]. The diversity of resource analysis techniques is a positive sign of research progress that yet provides challenges. Many of the new techniques have been developed for specific analysis questions, often inspired by available event data in a bottom-up fashion. This poses the problem of a fragmented and scattered research landscape of resource analysis. Nevertheless, some efforts have been made to review techniques for resource analysis.

A first comprehensive study on using and representing (primarily human) resources in existing process execution systems was given by Russel et al. [46], who studied how resources are integrated into workflow systems. Their work provides a resource metamodel and a collection of patterns to create, pull, push, and detour tasks to resources, however, without considering resource analysis based on execution data. Cabanillas et al. [13] examine research on resource handling in process- and resource-oriented systems, providing a framework with a selection of representative studies. The representative studies are categorized into *resource assignment* (defining resource requirements for process activities at design time), *resource allocation* (assigning specific resources to tasks during runtime), and *resource analysis* (evaluating process execution with a focus on resources). Exhaustive or systematic literature studies are provided for resource assignment, such as Oyang et al. [41], and resource allocation, such as Arias et al. [7] and Pufahl et al. [45]. However, a systematic review of the field of resource analysis is still missing. By looking at existing works, different resource analysis types are supported, such as the collaboration between resources [30] or work prioritization patterns by resources [52]. So far, there is no structured overview of the analysis concepts for identifying existing solutions, understanding the relation between the concepts, and stimulating future research.

This paper addresses this research problem by conducting a systematic literature review (SLR) to organize the scattered landscape of the state-of-the-art resource analysis in process mining. Our primary focus is on the following research goals: (1) *structuring the analysis concepts for resources in business processes*; and (2) *identifying the design approaches of the works.* By following these research goals, we lay the foundation for a conceptual framework of resource analysis in process mining. We identified 29 studies that addressed 27 different resource analysis concepts, which could be categorized into task-, relation-, and actor-oriented concept types as either directly or indirectly observable phenomena. Moreover, we divided the literature based on their primary design approach. To this end, our framework highlights the need to advance resource analysis in process mining by applying existing theoretical constructs.

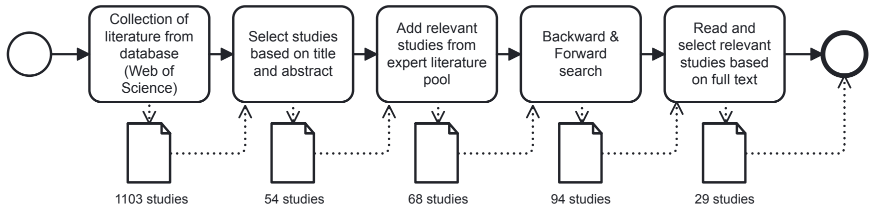
The rest of the paper is structured as follows. Section 2 discusses the importance of *resources* in related scientific disciplines. Section 3 describes our research method. Section 4 presents the results from the SLR, which are subsequently discussed in Section 5. Our work is concluded in Section 6.

2 The Notion of a Resource

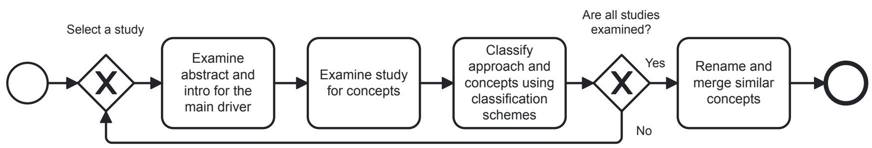
The term *resource analysis* requires some clarifications. To this end, we provide a brief background on the multifaceted nature of resource analysis, tracing its origins in organization science, management, and BPM. This context supports the understanding of the results of the literature review. In organization science and management, resources are often viewed as any physical or non-physical capital or assets a business may utilize to achieve a competitive advantage (e.g., [8]). Yet, a precise definition and its role in resource analysis depend on the theoretical discourse. The *VRIO* framework evaluates the internal resources of a firm based on their strategic value to achieve a sustained competitive advantage [8]. More recent work emphasizes the social aspects of inter-organizational collaboration and discusses how sharing of resources can lead to strategic advantages (e.g., [29]). Social network analysis [49] is closely related to these discussions and has found use in computer science.

BPM, in turn, is a collection of techniques and concepts to improve the operational performance of organizations by managing their processes throughout their lifecycle [23]. Here, resources are referred to as both human and non-human actors of activities in a process [23, p. 96]. The main focus has been on the process activities and their control flow, for which the resource perspective has played a secondary role. However, several research works have explicitly addressed this gap in the last decade. On the one hand, the modeling of resources has been targeted to support the definition and visual representation of certain resource needs of the process activities, for example, by extending process models with advanced role-based access control rules [51] or the graphical modeling language RAlph specifying advanced resource selection constraints [14]. Further, a general understanding of resource characteristics and attributes was developed [41]. On the other hand, the allocation of resources to tasks, where the best fitting resource for performing an activity is selected, has been researched for process automation solutions. To support this, different allocation patterns (e.g., [46]), allocation techniques (for an overview see [45]), and systems (e.g. [32]) have been created. Certain techniques also use insights from resource analysis, such as the measurement of team effectiveness for team assignment [37].

With the rise of process mining as a sub-domain of BPM, the support of analyzing resources in business processes and their behavior using event logs [2] has emerged. There are two main directions in this context: *organizational mining* and *resource behavior mining*. Organizational mining considers the relational or social structures of organizations, where social network analysis concepts [49] are commonly applied to investigate, for instance, social interactions (e.g., [3]), team discovery (e.g., [47]) or role mining (e.g., [12]). On the other hand, resource behavior mining studies the behavioral patterns of resource units, meaning *how* resources execute work. These concepts are predominantly quantitative representations of concepts from social science, organizational science, or BPM, such as the measurement of resource collaboration [43] or batching behavior [39].



(a) Search and selection.



(b) Extraction and classification.

Fig. 1: Literature review procedure.

3 Research Method

This section describes the SLR methodology we adapted from Kitchenham [35]. This specific methodology was explicitly developed to suit the needs of computer science. It provides support for a descriptive review with a clear scoping and qualitative analysis [42], which meets the objective of our research.

Figure 1 outlines the SLR process in this work, which we describe in the subsequent sections. Section 3.1 formulates the research objectives. Section 3.2 describes the literature search and selection procedure. Section 3.3 illustrates the extraction and classification procedure.

3.1 Research Objectives

This review aims to structure state-of-the-art resource analysis methods in process mining. We approach this objective by formulating the following research questions:

RQ1 What type of resource-related organizational and behavioral patterns can be analyzed using current process mining resource analysis methods?
RQ2 What design approaches were used in the literature to create the resource analysis methods?

The first research question (RQ1) aims to provide an overview of current resource analysis methods and to what extent process mining can capture various resource-related phenomena. RQ1 also identifies gaps for future research. The second research question (RQ2) concerns the premises on which a method was grounded. Specifically, it investigates to what extent a method was rooted in an existing theory, a hypothetical construct or idea, a business problem, or if it was technique-oriented.

3.2 Literature Search & Selection

We structured the literature extraction process in five distinct steps, as depicted in Fig. 1a. First, in *step 1*, we utilized a keyword search using the *Web of Science database*, using the following query of keywords: *TS=("Process Mining" OR "Business Process") AND TS=(resource$ OR staff OR personnel OR employee$ OR workforce) AND TS=(analysis OR analytics OR metric$ OR measurement$ OR indicator$ OR behavio$ r OR performance) AND LA=(English)*. The term "TS" indicates the search to include title, abstract, author keywords, and *keywords plus*[5]; and the term "LA" indicates the language of the study. The search was first done in November 2022 and included papers published within the years 1994 and 2022. The search was then extended in February 2024 to further include the years 2023 and 2024. We want to note that the two searches were executed based on different institutional subscriptions, which may lead to different outcomes for the same query.[6] Furthermore, we used only one database to keep the article within scope. Nonetheless, the Web of Science is one of the largest multidisciplinary databases (cf., [16, p. 3]). Step 1 resulted in 1,103 studies.

The literature selection (steps 2, 4-5) was guided by the following inclusion (IN) and exclusion (EX) criteria:

IN1 The study proposes at least one novel process mining *technique*[7] for extracting and analyzing a behavioral or organizational pattern in event logs from a resource perspective.

EX1 The study can be replaced by an extended or complete publication.
EX2 The study solely proposes an event log preparation technique.
EX3 The study focuses on another perspective, such as control flow.
EX4 The study proposes primarily a simulation model or a resource allocation mechanism.
EX5 The study proposes an approach that requires additional input, such as survey-based data or declarative models.

In *step 2*, we analyzed the title and the abstract of each study from the resulting 1,103 studies from the keyword search. We used the inclusion and exclusion criteria above as a guidance to select potentially relevant studies. Step 2 resulted in 54 studies.

[5] Index terms from *Web of science*, please see: https://webofscience.help.clarivate.com/en-us/Content/wos-core-collection/wos-full-record.htm (accessed: 2024-08-26).

[6] https://support.clarivate.com/ScientificandAcademicResearch/s/article/Web-of-Science-Search-in-All-Databases-refined-by-an-individual-database-may-return-more-results-than-the-same-search-in-that-individual-database?language=en_US (accessed: 2024-08-26).

[7] We define a *technique* according to the classification framework of information systems development methodologies by Iivari et al. [33] as a "well-defined sequence of elementary operations that more or less guarantee the achievement of certain outcomes if executed correctly" [33, p. 186]. In other words, a technique could be a simple function, a metric, an algorithm, or similar. A technique is to be differentiated from higher abstraction levels development methodologies starting with *methodologies*, continuing with *approaches*, and after that *paradigms* on the highest level [33, p. 186]. In the context of resource analysis, examples of techniques are the *handover of work* metrics by Aalst et al. [3] and the *competence* measure by Huang et al. [30, pp. 6461-6462]. We use the terms *technique* and *method* interchangeably in this article.

In *step 3*, we then added 14 relevant studies from our existing expert pool. The expert pool is a collection of articles gathered from multiple research projects concerning resource-related topics in BPM and process mining we and colleagues have participated in for more than a decade. This step was necessary because most relevant articles are hard to find through a keyword search. The essential vocabulary to distinguish different resource-related directions in process mining and BPM (cf., resource allocation, and resource analysis) has yet to be established. Note that, compared to previous steps, we did not explicitly apply the inclusion and exclusion criteria. The reason for this was to include these studies in the backward and forward search, because of their high thematic relevancy. Nevertheless, the inclusion and exclusion criteria were still applied to these papers in the final selection step. Step 3 resulted in 68 studies.

In *step 4*, based on the 68 studies from the previous step, we conducted a backward and a forward search using the Web of Science and Scopus[8]. Step 4 resulted in 94 studies.

Finally, in *step 5*, we read all the resulting 94 studies from the previous step based on their full text and then selected relevant studies using the inclusion and exclusion criteria from above. The complete literature search yielded 29 relevant studies.

The entire literature search and selection procedure was designed by all three authors and conducted by two. The studies used as input for the final step (step 5) were discussed by all three authors before final selection.

3.3 Data Extraction & Classification

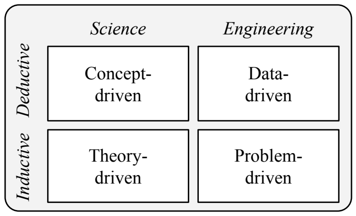
In the classification process, we wanted to investigate the *main* driver for developing the respective approaches and *what* type of concepts[9] they can analyze. A challenge with classifying the different approaches is the lack of consistency in definitions and a shared vocabulary in the broader context. A single concept can often have various names, or multiple concepts can be hidden under one term. In addition, ideas borrowed from other disciplines may only have a tenuous connection to their original definition. To find commonality, we developed two classification schemes (Fig. 2). We describe these schemes below before explaining their application in this work.

The first scheme (Fig. 2a) was inspired by the differentiation of descriptive and prescriptive knowledge in design science research [27]. We developed four classes depending on the type of inference (deductive or inductive) and research focus (science or engineering):

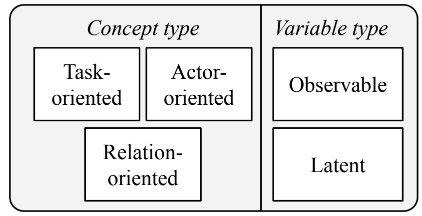
- *Data-driven approaches*: are created to explore the technical possibilities of extracting insights from a data set.
- *Problem-driven approaches*: are created as a direct solution to a business problem.
- *Concept-driven approaches*: are based on an existing resource-related concept.
- *Theory-driven approaches*: are based on a resource-related theory or theoretical framework.

[8] https://scopus.com (accessed: 2024-08-26).

[9] We refer to a *concept* as a resource-related behavioral pattern that an author aims to measure, directly or indirectly, using some technique. In the literature, other termonologies are often used and sometimes interchangeably, such as *notion*, *construct*, or *perspective*.



(a) Design approach



(b) Concept

Fig. 2: Classification schemes.

The second scheme (Fig. 2b) comprises two dimensions to classify the concepts that the approaches address. The first one defines three types of concepts, as inspired by theories on socio-technical systems (e.g., [11]):

- *Task-oriented concepts*: Patterns that emphasize how work is executed rather than the resources that execute them.
- *Relation-oriented concepts*: Patterns that emphasize relational, organization-structural, or transactional aspects of work.
- *Actor-oriented concepts*: Patterns that emphasize the resources and their attributes rather than the work they execute.

The other dimension divides concepts depending on their variable type (see Fig. 2b):

- *Observable*: The concept is directly measurable.
- *Latent*: The concept is only in-directly measurable.

The extraction and classification procedure, in which we applied the classification schemes above, is illustrated in Fig. 1b (p. 4) and described in the following. For each study, we first read the abstract and the introduction to identify the *main* driver for their work. Second, we identified the resource analysis concepts by analyzing the full text of the study. Third, we applied our classification schemes (Fig. 2) to classify both the main driver of the approach and the identified concepts. We additionally indicated whether a concept is *primary*, i.e., a prominent contribution of work, or *supporting*, i.e., integrated into the primary solution to enhance it.

After analyzing all studies, we finally grouped similar concepts under one terminology to enhance clarity and understandability. We also deliberately excluded concepts related to similarity measurements, often named as *importance*, *relatedness*, *similarity*, *distance*, and *dependency* measures, as they are primarily statistical techniques integrated into different types of resource analysis methods. Furthermore, we have not considered the concept of *resource profiles*, as it is a collection of diverse measures rather than a specific technique.

4 Results

This section describes the result of the SLR. Section 4.1 provides some metadata of the resulting 29 studies. Section 4.2 discusses the concepts identified in the literature. Section 4.3 closes by discussing the design approaches used in development.

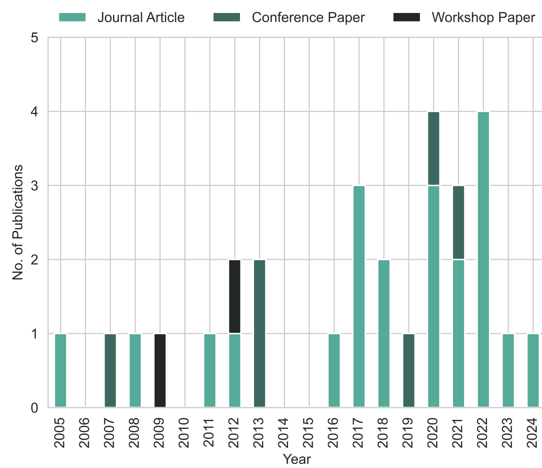


Fig. 3: Overview of relevant studies according to publication year and type.

4.1 Overview of Selected studies

The SLR resulted in a selection of 29 relevant studies. As illustrated in Fig. 3, there has been an overall slight increase in studies since 2005. Most of the studies identified in this SLR were published in journals (21 studies), followed by conferences (six studies) and workshops (two studies). Moreover, the journals that published more than two studies according to our observation are *Decision Support Systems* (four studies), *IEEE Access* (two studies), and *ACM Transactions on Management Information Systems* (two studies). In contrast, the most common venues among the conference and workshop studies were *Business Process Management* (two studies) and *Business Process Management Workshop* (two studies).

4.2 Resource Analysis Concepts

In this section, we approach the first research question (RQ1): *What type of resource-related organizational and behavioral patterns can be analyzed using current process mining resource analysis methods?* We identified 27 resource analysis concepts from the 29 studies, all classified into one of three concept types (task-, relation-, or actor-oriented) and according to variable type (observable or latent). Table 1 illustrates the result of this classification. Fig. 4 extends Table 1 with a graphical overview of the total number of primary and supporting concepts according to concept and variable type. We elaborate on this result in the following subsections.

Table 1: Concept-matrix (●: *Primary concept;* ○: *Supporting concept*).

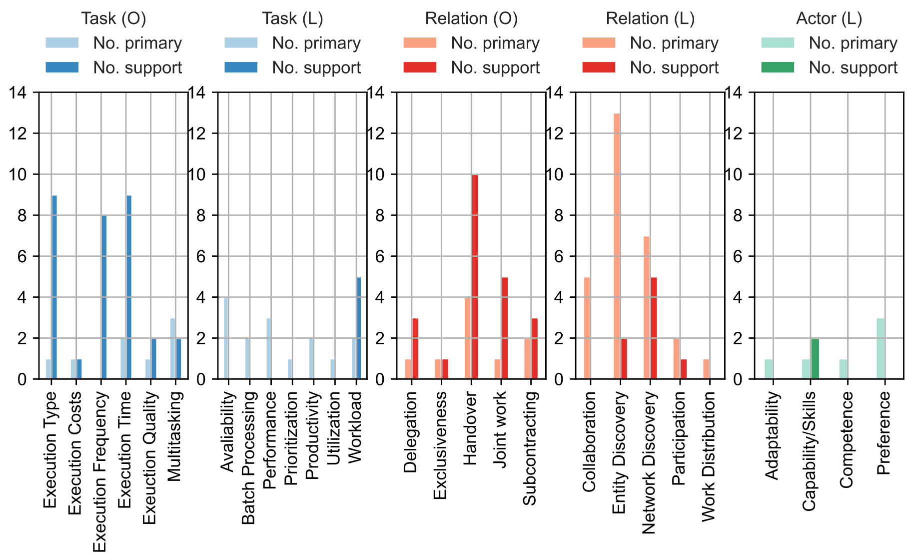
Concept type	Task													Relation										Actor				
Variable Type	*Observable*						*Latent*							*Observable*					*Latent*					*Latent*				
Concepts	Execution Type	Execution Costs	Execution Frequency	Execution Time	Exeuction Quality	Multitasking	Avaliability	Batch Processing	Performance	Prioritization	Productivity	Utilization	Workload	Delegation	Exclusiveness	Handover	Joint work	Subcontracting	Collaboration	Entity Discovery	Network Discovery	Participation	Work Distribution	Adaptability	Capability/Skills	Competence	Preference	
No. primary (●)	***1***	***1***	***-***	***2***	***1***	***3***	***4***	***2***	***3***	***1***	***2***	***1***	***2***	***1***	***1***	***4***	***1***	***2***	***5***	***13***	***7***	***2***	***1***	***1***	***1***	***1***	***3***	
References / *No. support (○)*	*9*	*1*	*8*	*9*	*2*	*2*	*-*	*-*	*-*	*-*	*-*	*-*	*5*	*3*	*1*	*10*	*5*	*3*	*-*	*2*	*5*	*1*	*-*	*-*	*2*	*-*	*-*	**Design Approaches**
[3] van der Aalst et al. (2005)														●/○		●/○	●/○	●/○			●							Data-driven
[34] Jin et al. (2007)	○																			●		○						Problem-driven
[50] Song & van der Aalst (2008)																○	○	○		●/○	●							Data-driven
[40] Nakatumba & van der Aalst (2009)				●/○					●				●/○															Theory-driven
[60] Yingbo et al. (2011)						●																						Concept-driven
[26] Ferreira & Alves (2012)																	○			●	○							Data-driven
[30] Huang et al. (2012)		○					●						○						●							●	●	Concept-driven
[12] Burattin et al. (2013)																●/○				●								Concept-driven
[36] Kumar et al. (2013)																○			●									Problem-driven
[61] Zhao et al. (2016)		●		●	●											○			●					●				Data-driven
[39] Martin et al. (2017)				○				●																				Concept-driven
[43] Pika et al. (2017)	○		○	○	○	○			●		●	●	○	○			○		●						●		●	Problem-driven
[52] Suriadi et al. (2017)										●																		Data-driven
[5] Appice (2018)																	○			●	●/○							Data-driven
[57] Ye et al. (2018)	○																			●	●/○							Data-driven
[10] Bidar et al. (2019)	○												○	○		○									○		●	Concept-driven
[19] Delcoucq et al. (2020)			○																	●								Data-driven
[38] Martin et al. (2020)				○			●																					Problem-driven
[53] Tan et al. (2020)																○				●	●/○							Problem-driven
[54] Utama et al. (2020)				○			●																					Data-driven
[20] Deokar & Tao (2021)															●/○	●/○		●/○		●								Data-driven
[24] Estrada-Torres et al. (2021)				○		●	●																					Data-driven
[56] Yang et al. (2021)	○		○	○	○				●		●		●			○			●			●	●					Problem-driven
[31] Hulzen et al. (2022)	○			○		●/○														●								Problem-driven
[44] Pika et al. (2022)	○		○					●																				Concept-driven
[55] Yang et al. (2022)	●/○		○																	●/○		●						Data-driven
[58] Yeon et al. (2022)			○																	●	●/○							Problem-driven
[18] Delcoucq et al. (2023)			○																	●								Data-driven
[21] Diamantini et al. (2024)	○		○	○									○			●/○					●				○			Data-driven

Task-oriented Concepts. The task-oriented concepts focus on the work rather than the resources utilized for it. More specifically, these concepts aim to answer *how* or *how well* work is executed. In this category, we identify 13 concepts, six of which are directly observable and seven of which are latent.

Observable: Task-oriented concepts that are directly observable are various metrics to count or measure work-related properties in the log. *Execution type*[10] comprises various metrics and concepts that measure the amount of work executed by a resource unit related to a specific type of execution, such as the indicator "distinct activities" by

[10] All concepts starting with the term *execution* are umbrella terms for multiple metrics with or without specific concept names. An example is Pika et al. [43], who propose multiple *execution frequency* metrics to measure the concept *utilization*, such as the indicators "activity completions" and "number of case completions" to count the instance involvement of a resource on an activity and case level respectively [43, p. 1:9].

Fig. 4: Overview of the number of primary and supporting concepts according to concept type and variable type (O=observable variable, L=latent variable).



Pika et al. [43], which counts how many activities of a certain type was executed by a resource [43, p. 1:9]. *Execution costs* measures the cost of work [30,61]. *Execution frequency* measures activity frequency, yet independent of activity type or property, such as the indicators "activity completions" by Pika et al. [43, p. 1:9] or "amount-related productivity" by Yang et al. [56, p.352]. *Execution time* comprises metrics measuring various time aspects, such as "processing speeds" according to Nakatumba & van der Aalst [40, p. 8] or other notions of execution durations (e.g., [21,24]). *Execution quality* refers to any property that measures the quality of work, often related to the quality of the execution itself [56,61] or customer satisfaction [43]. Lastly, *multitasking* measures a resource's simultaneous engagement in multiple or parallel activities [24,31,43,60].

Latent: Task-oriented concepts that are indirectly observable combine or extend behavior indicators to provide a deeper analysis of the work executed. *Availability* measures when a resource is available for work and includes concepts such as *shift work* [54] and timetabling [24]. *Batch processing* investigates how resource units organize their work in batches [39, 44]. *Performance*[11] comprises methods and indicators measuring how well work is executed in terms of *efficiency* [40, 43, 56]. On the other hand, *productivity* comprises methods and indicators to measure how well a resource unit performs in terms of *effectiveness*, i.e., outcome- and goal-oriented [43, 56]. *Prioritization* investigates how resource units order the execution of tasks [52]. *Utilization* comprises descriptive measures of what a resource unit is *actually* doing [43, p. 1:8].

[11] *Performance* and *productivity* are often used interchangeably in the literature. Yet, we aimed to separate these concepts.

Finally, *workload* measures the work done by or assigned to a resource unit within a time period (e.g., [30, 40, 43, 56]).

Fig. 4 shows that the most common primary task-oriented concepts are *multitasking* (3 studies), *availability* (4 studies), and *performance* (3 studies). The most commonly supporting concepts are *execution type* (9 studies), *execution frequency* (8 studies) and *execution time* (9 studies). Most supporting concepts are observable rather than latent, which is to be expected. An exception is the concept *workload*. The reason for this is likely that the concept is well-established in the process mining literature. *Execution frequency* is another outlier, as it is only observable as a supporting concept.

Relation-oriented Concepts. The relation-oriented concepts focus on relational patterns between entities in the data, such as resource-activity or resource-resource patterns. These concepts concern the socio-structural aspects of work, such as how work is transferred between resources or how resources are related to one another. We identified ten concepts in total in this category; five are directly observable, and the other five are latent.

Observable: The observable relation-oriented concepts are often metrics that measure task transferals and executions between multiple resources. *Delegation*[12] comprises metrics that count how many tasks, within their lifecycle, were transferred from one resource to another for further processing [3, p. 560], often requiring event log properties about activity transitions such as *assign*, *reassign*, or *schedule* [1]. *Handover*[13] metrics measure how often work is directly or indirectly transferred from one resource unit to another after task completion (e.g., [3, 21]). *Exclusiveness*, on the other hand, is an "anti-handover" measure, as it measures how often work was *not* transferred between resources [20, p. 759]. *Joint work*[14] measures how often the same type of work was executed by different research units, either on an activity level or a case level [3, p. 560]. *Subcontracting* measures the work executed "in-between" resource units [3, p. 560].

Latent: The latent relation-oriented concepts can be divided into two streams of concepts. The first stream of concepts aims to discover and analyze organizational models: *Entity discovery*[15]comprises methods that identify new resource entities such as roles [12,34,53,57,58], groups and teams [18–20,31,50,55], or communities [5,26,57], and *network discovery* utilizes techniques from social network analysis to create and analyze social networks of resource units (e.g., [50, 57, 58]). The other stream of concepts considers work-related aspects but is viewed from a social perspective: *Collaboration*[16] assesses how well resources communicate or work with other resources

[12] *Delegation* is often referred to as *reassignment* (e.g., [3]) or *previous owner* [10, p. 414] in the literature.

[13] *Handover* is an umbrella term for different handover relation concepts, such as *handover of work* [3,21,50,53,56], *handover of roles* [12], or simply *hand-offs* [36] or *handovers* [10]. Some work are less explicit (e.g., Zhao et al. refers to "transfer [of] work-items" [61, p. 309]).

[14] *Joint work* refers to metrics based on "joint activities" or "joint cases" (cf., [3, p. 560]).

[15] *Entity discovery* is an umbrella term. The methods in this category are commonly named after the type of entity they discover.

[16] *Collaboration* includes the concepts *cooperation* and *compatibility*, as they are often used interchangeably in the process mining literature (cf., [36, 56]).

(e.g., [30, 36, 43]). *Participation* measures a resource unit's involvement in work compared to other resources, such as the indicator "attendance" [56, p. 350] and "group member contribution" [55, p. 8]. *Work distribution* examines how work is distributed among multiple resources within an organizational unit [56, p. 350].

The most common primary relation-oriented concepts (see Fig. 4) are *entity discovery* (13 studies), *network discovery* (7 studies), and *collaboration* (5 studies). The most common supporting concepts are *handover* (10 studies), *network discovery* (5 studies), and *joint work* (5 studies). *Handover* and *joint work* are often used for *entity* and *network discovery*. Moreover, both concepts, *entity* and *network discovery*, are often used complementarily. An example is creating social networks to discover communities [5, 57] or create social networks based on already discovered resource units [50].

Actor-oriented Concepts. The actor-oriented concepts focus on resources and their ability to pursue work. These concepts examine resource attributes with the aim of better understanding how to best employ them in work, with little emphasis on the work itself. We identified five concepts in total in this category, all latent. *Adaptability* concerns a resource unit's time to adjust to new tasks [61, p. 310]. *Capability* relates to the type of work a resource unit is able to perform, such as *skills* [21, 43] or *experience* [10, p. 414]. It is the only actor-related concept that is also used as a supporting concept (cf., [10, 21]). *Competence* measures how well a unit can perform a particular task [30, p. 6458]. Finally, *preference* estimates the type of work or work behavior a resource may prefer to execute over another [10, 30, 43]; or a resource unit's *preference* in working with another resource [10, p. 408].

Compared to the other concept types, *task* and *relation*, there is a lack of actor-oriented concepts. Among the four actor-oriented concepts, *preference* is the most prevalent. Note that the approaches proposed for this concept have varying degrees of complexity, ranging from simple metrics [30, 43] to machine learning methods [10].

4.3 Design Approaches

In this section, we approach the second research question (RQ2): *What design approaches were used in the literature to create the resource analysis methods?* Table 1 depicts the result from classifying each approach in one of four design approach types based on their primary driver for development (see Fig. 2a). We elaborate on this next.

Data-driven Approaches. Data-driven approaches explore the technical possibilities for extracting valuable insights from event logs. These investigate *what* insights can be retrieved, often by applying an existing technique, with minor emphasis on a specific problem or analytical phenomenon. We identified 14 studies in this category, making out nearly most of the publications. There is no clear tendency toward any stream of resource analysis or theme in the literature in this category. However, two possible outliers are [21, 61], as they are the only authors within this category that include an actor-oriented concept in their approaches.

Problem-driven Approaches. Problem-driven approaches start with a specific business problem for which no sufficient solution exists in process mining. We identified eight studies within this category. The authors in this category address the need for solutions to obtain objective insights about resources to improve managerial decision-making. There are three noticeable thematical tendencies in the literature. Three studies focus on creating resource profiles either as frameworks for combining various resource analysis metrics [43, 56] or with the aim to find profile similarities [31]. Four studies use resource analysis to provide decision support for resource assignment or allocation mechanisms [34,36,38,58]. The last study focuses on discovering possible information flow between organizations [53].

Furthermore, there is a difference in the type of actor as a focal point of the problem. On the one hand, [31, 43] analyze resources at a micro-level, i.e., single-unit resources such as employees or single machines. On the other hand, [31,34,36,53,56,58] address resource analysis at a meso-level, i.e., resources within a larger community comprising groups or roles. [53] explicitly examines actors as part of cross-organizational processes, thus setting them slightly apart from [31, 34, 36, 56, 58], as they concern smaller resource unit constellations.

Concept-driven Approaches. Concept-driven approaches implement or extend previous concepts in resource analysis from any relevant academic field. We identified six studies in this category. Focusing only on the proposed primary concepts, the most common ones in this category concern how work is organized, such as through multitasking or batch processing. Another common concept is *preference*. Huang et al. [30] propose multiple primary concepts, *preference* included, whereas Bidar et al. [10] explicitly advance the notion of *preference* using supporting concepts and machine learning.

Most concept-driven approaches expand on concepts from process and organizational science. Only Huang et al. [30] explores concepts explicitly from the social sciences, i.e., *preference*, *availability*, *competence*, and *cooperation* [30, pp. 6458-6459]. This is, to some extent, also true for [12] because of the utilization of social network analysis.

Theory-driven Approaches. Theory-driven approaches utilize an existing theory as a basis for a resource analysis method. We identified only one study in this category. Nakatumba & van der Aalst [40] translate the socio-psychological framework of stress-performance relation, also known as the *Yerkes-Dodson Law of Arousal and Performance*[17], into a process mining setting. This is achieved by applying the supporting concept *execution time* (processing speed) and *workload* to a linear regression model. As the Yerkes-Dodson law dictates the impact of mental arousals, such as stress and emotional pressure, on human performance, [40] assumed that the processing speed depends on the workload.

[17]In a strict sense, the Yerkes-Dodson law is not a theory but an empirical phenomenon in psychology (cf., [22]) based on the original findings by Yerkes and Dodson [59]. Nonetheless, the phenomenon is well-studied and has a long history in the psychological literature, often characterized as a U-curve-shaped model (cf., [22]). Hence, we have treated the law as a theory for our purposes.

5 Discussion

The result of our SLR provides an overview of the concepts in resource analysis that can be measured using process mining techniques. Based on this, in Section 5.1, we want to highlight some opportunities for future research. In Section 5.2, we discuss some of the limitations of our work.

5.1 Future Research

We have identified five directions for future work, which we discuss in the subsequent paragraphs.

Enhance Existing Concepts through Variation. As most concepts are abstract ideas of resource behavior, each provides an opportunity for future work through modification and variation. As implied in Table 1, it is already a common practice to leverage existing approaches by adapting the underlying mechanisms, e.g., changing metrics or using other techniques. Good examples are works that propose some *entity discovery* method. Burattin et al. [12] create roles by defining a version of handoffs called *handover of roles*. In contrast, Ye et al. [57] identify multi-role resources based on weighted community networks using social network analysis. Moreover, the concept of *preference* is another example. Huang et al. [30] base this notion on the activity type a resource has bid on within a time frame [30, p. 6460]. Pika et al. [43] view the concept as a category of multiple resource behavior indicators, such as *multitasking* [43, p. 1:10]. Bidar et al. [10] utilize machine learning methods to leverage the concept. All in all, every concept and associated techniques can be further modified and expanded upon, hence is an opportunity for further development in the future.

Leverage Actor-oriented Concepts. The most covered concept types are task-oriented and relation-oriented, whereas only a few authors have proposed an actor-oriented concept. A logical reason is that event data represents work-related states and transitions, and actor-oriented concepts concern a resource's innate ambition or ability to work. The latter is hard to measure with event data. Nevertheless, the authors within this category have shown that it is indeed possible to create process mining techniques that can measure more abstract behavioral patterns not explicitly provided by the data. An example of this is to measure the strength of *collaboration* between resources (e.g., [30,36,56]), collaboration, which is a rather complex social phenomenon. Whereas task-oriented and relation-oriented concepts tend to describe the actual work, actor-oriented concepts with associated techniques could provide a deeper understanding of the reasons behind behavioral patterns. Correspondingly, the outcomes from such methods can be used in other areas, such as process enhancement, simulations, and resource allocation, to facilitate a sense of realism in the analysis.

Utilize Theories and Concepts. There is a noticeable gap between theory-driven and concept-driven approaches. Resource analysis is a broad multidisciplinary topic, and other academic fields, such as organizational science or social sciences, have a rich theoretical basis from which future work could profit. The process mining literature already benefits from theories and concepts outside its domain to some extent. In organizational mining, many approaches borrow concepts from social network analysis (e.g., [3, 5, 26]). In resource behavior mining, Huang et al. [30] explicitly borrowed the concepts *preference*, *availability*, *competence*, and *cooperation* from social sciences. Moreover, Nakatumba & van der Aalst [40] based their approach on the Yerkes-Dodson Law, a social-psychological phenomenon. Nevertheless, only a few pieces of literature are *explicitly* theory- and concept-driven. We believe that future work could benefit from making explicit use of existing theories and constructs from other academic disciplines, such as the social sciences, to create new concepts or refine existing ones.

Apply Techniques to Behavioral Studies. Process mining techniques can be applied as methodologies in behavioral studies [28]. The medical domain has shown a special interest in this regard (e.g., [4, 17, 25]), as process mining provides simple and objective means to study complex behaviors in event data. Our work supports future authors with an overview of the different aspects of resource analysis and their corresponding literature. In addition, most authors reviewed in this work have also implemented their approaches in easy-to-apply process mining tools such as *ProM* [18] or *PM4Py*[19], making their contributions more accessible for both academic and practical purposes.

Establish the Resource Definition. A last remark can be said about the *resource* definition itself and how it may impact how to develop techniques and interpret their output for different data sets. Most approaches define a resource in broad terms, such as *any* human executing tasks in a process or even any performer, regardless of whether human or not. However, the resource type may significantly impact the interpretation of the result or even the validity of a technique. To give a simple example, the performance measure of a machine writing e-mails is not the same as the same measure of that of a human for the same task. Machines execute such tasks in near-zero time, whereas humans require minutes, hours, and days. Similarly, for concepts like *collaboration*, where at least two resources are involved, there is a critical distinction to make when the concept concerns only humans, as when they concern human-machine interactions or that of only machines. Even on a fine-granular level, where resource types may be slightly different, such as the distinction between a doctor and a nurse, may have a significant influence on how we should develop techniques and interpret their results. Defining such nuances and creating techniques accordingly is an exciting future research direction in resource analysis.

5.2 Limitations

The first limitation of our work regards the selection procedure. We collected the literature from a single database using rather restrictive search criteria focusing on studies

[18] https://promtools.org (accessed: 2024-08-26).
[19] https://processintelligence.solutions (accessed: 2024-08-26).

presenting process mining techniques with similar requirements. The reason for this was to stay within the scope of this work but also to simplify classification, yet this came at the cost of important work on resource analysis (e.g., from BPM and Role mining [9, 15, 47, 48]). We tried to mitigate this limitation through a backward and forward search and by including additional studies using expert knowledge. The second limitation relates to the extraction and classification procedure concepts. As many concepts are abstract behavioral constructs not sufficiently defined in the literature, the classification procedure is a difficult task prone to subjectivity. Correspondingly, some similar techniques refer to different concepts, further challenging the classification process. To mitigate these problems, we discussed the classification within our research team and adapted the terminologies or created umbrella terms.

6 Conclusion

In this work, we conducted an SLR to identify resource analysis concepts in process mining and their primary driver for development. We found 27 resource analysis concepts in 29 studies, which can be classified as task-oriented, relation-oriented, or actor-oriented concept types. They can also be discriminated in observable or latent variable types. Furthermore, four design approaches distinguish the approaches: data-driven, problem-driven, concept-driven, and theory-driven. Most concepts are data- and problem-driven. Only one author developed a theory-driven approach. Future work can create new approaches by advancing existing ones, e.g., changing the underlying technological foundation or creating new resource analysis tools grounded in theories from other disciplines.

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