# Automatic Resource Allocation in Business Processes: A Systematic Literature Survey

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For delivering products or services to their clients, organizations execute manifold business processes. During such execution, upcoming process tasks need to be allocated to internal resources. Resource allocation is a complex decision-making problem with high impact on the effectiveness and efficiency of processes. A wide range of approaches was developed to support research allocation automatically. This systematic literature survey provides an overview of approaches and categorizes them regarding their resource allocation goals and capabilities, their use of models and data, their algorithmic solutions, and their maturity. Rule-based approaches were identified as dominant, but heuristics and learning approaches also play a relevant role.

CCS Concepts: • **Applied computing** → **Business process management**; **Business intelligence**; *Business process management systems*; *Operations research*; Multi-criterion optimization and decision-making.

Additional Key Words and Phrases: business process, resource management, resource allocation, optimization, literature review

**ACM Reference Format:**
Luise Pufahl, Sven Ihde, Fabian Stiehle, Mathias Weske, and Ingo Weber. 2021. Automatic Resource Allocation in Business Processes: A Systematic Literature Survey. 1, 1 (July 2021), 28 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

## 1 INTRODUCTION

Business Process Management (BPM) is applied by organizations to run their operations in an effective and efficient manner. It is a management paradigm positioning business processes, which consist of a set of connected activities carried out to reach a certain business goal [58], in the center of its efforts to facilitate excellence in the execution of business processes and their continuous improvement. For a successful execution of business processes, organizations need a rich set of resources, such as human resources, machines, vehicles, materials etc. [8, 29]. Often resources are valuable assets, frequently costly and limited [3], such that the success and loss of a business process is closely intertwined with the efficient use of resources. The challenge thereby is that resources are not only involved/required in one single process case of a single business process, but in several cases of several different business processes, which may run concurrently [68]. Consider the case of a physician who has to diagnose and treat all kind of different patients during the day. The physician is not only involved in the treatment processes but also in the reimbursement processes of a hospital, in which patients or their health insurers get invoiced.

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Manuscript submitted to ACM

Resource allocation aims at ensuring that each activity of a certain process case (i.e., a task) is executed at the right time and with the right resources [8, 35]. Resource allocation for business processes can be viewed as a multi-objective decision-making problem [71], which involves the following key aspects:

- Each business process has certain time, cost, and quality goals which need to be reflected while allocating process tasks to resources [63].
- Multiple processes and process cases run concurrently, such that conflicts requesting the same resources have to be resolved and imbalances between the workload of resources handled [68].
- The focus of business processes is typically not on a single resource or unit of work, but on the coordination across activities to reach a business goal; constraints regarding the order of process activities need to be considered [63].

Due to the importance and complexity of resource allocation problems in business processes, in recent years a multitude of approaches have been developed to provide (semi-) automatic support. The variety of approaches support different optimization goals, such as minimizing the cycle time or process cost, balancing the resources' workload, or finding the best-fitting resource. Most approaches support 1-to-1 allocations (i.e., one resource to one task), e.g., [3, 24, 27, 32]. Some provide approaches for many-to-1 allocations, e.g. [23, 43], where the capacity of a resource may be greater than one, and 1-to-many allocations [14], where a team of resources is needed to solve a task. A few approaches support also many-to-many allocations, where a set of resources can work on a set of tasks [47, 56]. With the availability of historic business process execution records in form of event logs [55], not only business process models but also process data has been more and more explored for supporting advanced resource allocation in business processes; for instance, to learn resource working preferences [2] or resource allocation rules from historic logs [37]. Different algorithmic approaches are applied for supporting resource allocation in processes, including rules and logic programming (e.g., [7, 8]), trained rules (e.g., [37]), linear programming (e.g., [56]), heuristics (e.g., [16]), genetic algorithms (e.g., [27]), and machine learning approaches (e.g., [29]). Some approaches only support local optimization for a specific process case with the risk of arriving at a sub-optimal solution, whereas a broad range of approaches also support global optimization for allocating resources to business cases, also considering different priorities of the process cases.

The high variety of approaches and techniques for resource allocation in business processes would render a systematic overview valuable for researchers and stakeholders. Such a systematic overview should help researchers in acquiring an complete view of the solution space, and a categorization of solutions and their maturity will be beneficial for finding open research challenges. For process stakeholders, the systematic overview should provide a guidance in selecting the right algorithmic approach for their business scenarios.

Existing literature studies in the area of resource allocations in business processes [3, 8] either focus on resource management in more general, have studied less works, or did not discuss in detail the targeted resource allocation problems and solution approaches. Thus, in this study, we want to fill this research gap and provide a detailed review of automatic approaches for resource allocation in business processes by discussing their capabilities, optimization goals, input data, applied techniques, evaluation, and available prototypes. This work follows a methodology for rigorous and replicable systematic literature reviews (SLRs) as specified by Kitchenham [33].

By searching in four databases and with the help of a backward and forward search, we have identified 49 relevant studies in this review. Resulting from various countries, they were mainly published within the last 10 years. Most of the identified resource allocation approaches in this review aim at assigning one task to exactly one resource (but approaches supporting many-to-1, 1-to-many, and many-to-many were also found) and have process-oriented resource allocation goals, such as minimizing the process costs or finding the best-fitting resource. This review shows the role of process models and data in the approaches and provides a taxonomy on the used resource and task attributes for the resource allocation. The review provides insights into the different applied solution techniques and exhibits that mainly rules, heuristics, and machine learning approaches are used, but also linear programming. Lastly, the review shows that many studies evaluate their approaches with simulation experiments and only a few approaches provide prototypical implementations. Based on these results, this review provides an overview, a discussion of the state of the art, and deduces areas for future research.

In the remainder of this paper, first, a background on resource allocation in business processes is given in Section 2 and the related work is presented in Section 3. Then, the applied research method –the SLR protocol– is explained in Section 4. The resulting studies of the SLR are presented in Section 5 where the different resource allocation capabilities and goals, applied algorithmic solutions, and the maturity of the approaches are analyzed. Based on the results, their implications are discussed, along with open research fields and limitations of the research, in Section 6. Finally, conclusions are drawn in Section 7.

## 2 BACKGROUND

To achieve its business goals, each organization has to run a set of business processes which are executed with the help of different resources, such as humans, IT services or machines (as shown in Figure 1). In the following section, we present the essential concepts of business processes, resources and their allocation.

### 2.1 Business Process

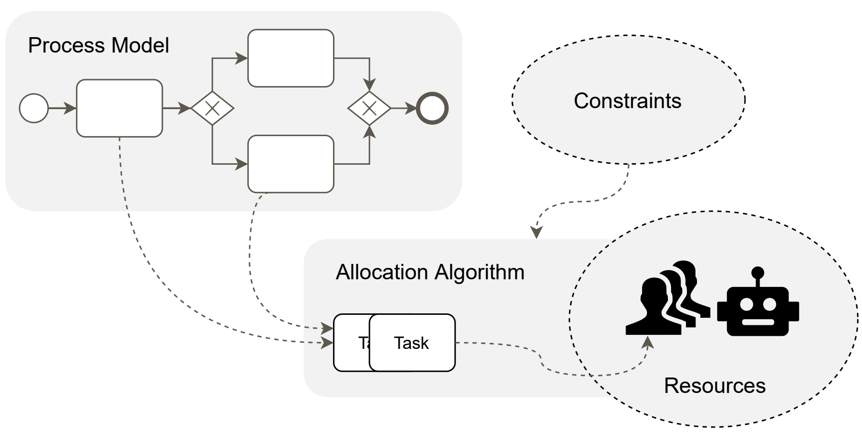



Fig. 1. An organization with its business processes and resources where tasks resulting from process executions need to be allocated to resources.

A business process of an organization consists of a set of activities which are coordinately executed in an organizational and technical environment to reach a certain business goal [58, Chapt. 1], e.g., providing the blood test results for a given blood sample. For managing the documentation, redesign, execution, monitoring, and analysis of a business process, often process models are used as formal representation of a business process. Figure 2 shows an example process model given as BPMN (Business Process Model and Notation) diagram [41] of a hospital laboratory. The process is initiated as soon as a blood sample is received. Then, it is registered by a lab assistant, and, next, prepared by a lab assistant. In a next step, the prepared blood sample is analysed by the blood analysis machine. If no error occurred the result can be published at the hospital information system or the analysis has to be repeated. Formally, a process model is defined as follows:

*Definition 2.1 (**Business Process Model and Instances**).* A business process model consists of a set of activities, gateways and events, which are connected by control flow edges. The process starts as soon as the start event is triggered. When the goal of the process is reached, the process is terminated by an end event. A business process model acts as a blueprint for a set of business process instances. A process instance represents one concrete execution of the process model.

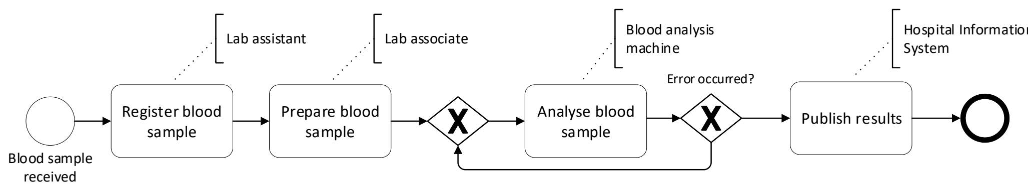



Fig. 2. Laboratory process of an hospital given as BPMN process diagram with the information on resources in the activity annotation.

For specifying a process model, different process modeling languages are available, such as the BPMN standard [41] specified by the Object Management Group, Event-driven Process Chains (EPCs) [48] or Petri net [58, Chap. 4] as rather formal specification language. As illustrated by the example process, we find the set of activities and their order in the given BPMN diagram to reach a specific business goal, e.g., providing blood analysis results. For a concrete process instance, activity instances are instantiated during run-time, which need time and resource(s) to be executed. In this paper, we call them tasks.[1]

Each task follows a specific life cycle [58, Chap. 3]: After it has been initialized, it is ready for its execution as soon as it is triggered by its incoming control flow edge. Then, it is allocated to one resource or several resources. At a certain point, it is started by the allocated resource(s), and after the work has been done, it is completed. Furthermore, each task has specific characteristics, task data (e.g., due date), based on which allocation to resources can be made.

Reaching a business goal is typically the main objective for an organization, but also how the goal is reached, i.e., that a process is executed efficiently (with a good performance) by its resources. *Process performance* can be measured with regards to time, cost, and quality [17, Chap. 6]. A relevant time-related measure is the *cycle time*, which measures the time between the start and end of a process instance (i.e., processing time plus the waiting time between activities) [17, Chap. 7]. Process costs are usually calculated by measuring the time used to execute a task and multiply it with cost per time unit of the respective resource. The quality can be identified by calculating, for instance, the rate of successful executed process instances.

When business processes are supported in their execution by an information system or a Business Process Management System (BPMS), then process execution data is stored, from which event logs can be generated [44]. Event logs are useful for an evidence-based process analysis with the help of process mining techniques, such as the automated discovery of process models or the enhancement of process models by resource information [55]. An event log consists of a series of events for different process cases reflecting, e.g., the start or completion of a task. An excerpt of the event

[1]Please note that this definition of a *task* is different to the BPMN standard [41], in which it is defined as single unit of work in a process diagram, whereas we define a *task* as an activity instance of a process instance.

Table 1. Illustration of the event log structure

| case id | timestamp | task | lifecycle state | resource |
|---|---|---|---|---|
| ... | ... | ... | ... | ... |
| 9845 | 14/01/2021 11:22 | Register blood sample | start | Lab assistant |
| 9845 | 14/01/2021 11:25 | Register blood sample | complete | Lab assistant |
| 9852 | 14/01/2021 11:26 | Register blood sample | start | Lab assistant |
| 9852 | 14/01/2021 11:30 | Register blood sample | complete | Lab assistant |
| 9845 | 14/01/2021 11:26 | Prepare blood sample | start | Lab associate |
| 9845 | 14/01/2021 11:32 | Prepare blood sample | complete | Lab associate |
| 9845 | 14/01/2021 11:40 | Analyze blood sample | start | Blood analysis machine |
| 9845 | 14/01/2021 12:09 | Analyze blood sample | complete | Blood analysis machine |
| ... | ... | ... | ... | ... |

log from the laboratory process shown in Figure 2 is represented in Table 1. Each event has a case id (e.g., `9845`) as reference to a process instance, a timestamp (e.g., `14/01/2021 11:22`) when the event has occurred, the executed activity (e.g., `Register blood sample`) and its lifecycle state (e.g., `start`), additionally, other data can be given, such as resource information (e.g., `Lab assistant`). Event logs can be, for example, imported into the process mining toolkit *ProM*, which offers a broad range of process mining techniques for discovery, conformance, and process analysis [31].

### 2.2 Resources and their Allocation in Business Processes

Resources are the fundamental basis for organizations in order to execute the tasks that are necessary to reach the goals of business processes. Depending on the background of the research the resource definition varies accordingly. In this work, we looked at all the different definitions provided [2, 5, 7, 9, 16, 20, 30, 45, 60, 62, 63, 65, 68, 72] and summarized them. According to them, we define a resource in the context of a business process is defined as follows:

*Definition 2.2* (***Resource***). Anything that is necessary to execute tasks is considered a resource (e.g. human, vehicle, software, tools etc.). A resource has a set of attributes describing the capabilities, capacities, and the availability of a resource at a given point in time. Its values might change during run-time. Resources can be subdivided into active and passive resources. Whereas an active resource describes anything that is able to execute tasks, the passive resource is used by another resource to execute a task. Most often, human resources or machines are classified as active resource, while tools are passive resources.

Resource allocation is the key principle of resource management in business processes [8]. Its goal is the assignment of a process task to the most appropriate resource among the available resources. In the selection of the most suitable candidate for the work, the characteristics and requirements of the to-be assigned task as well as the characteristics of the resources are considered [18]. Resource allocation in processes is a complex decision problem because organizations not only have one task to-be executed at a point in time but several ones, which carry different level of importance (i.e., a global optimization). For a rational resource allocation, the performance goals of business processes, such as minimizing time or costs, need to be considered in the resource allocation [68]. In addition, resource allocation in business processes is not only about the optimization on a single work unit but about a set of activities, which are connected in a specific order [63].

Traditionally, resource allocation is a manual effort in an organization where a human being assigns tasks to qualified resources (push principle), or the staff members select tasks on their own from a task list (pull principle) [46]. In operations management, the problem of allocating a resource to tasks has a very long tradition and is known as the *Assignment Problem*; it has been discussed in different versions [32].

In the BPM domain, BPMSs have been designed and studied that "control the execution of business processes instances, according to the logic defined in the respective process model." [18]. BPMSs mostly assign tasks to workers by a role-based distribution, where all workers get provided the task in their task list who are members of a specific role [46]. Although, this approach allows that only workers get a task who have the permission, it does not support an efficient resource allocation. The YAWL (Yet Another Workflow Language) engine that was developed to support various workflow patterns [54] has implemented a broad range of resource allocation patterns, such as capability-based distribution or history-based distribution, based on a comprehensive study by Russel et al. [46]. However, these mainly optimize the resource selection for a specific process case (i.e., local optimization) but does not consider the importance of other process cases. At the same time, research has started to use process models enhanced with additional information on resources, arrival times of instances etc. These are then used to find an optimized resource allocation with the help of techniques from operations management, such as with stochastic-branch-and-bound [16], linear programming [56], or a heuristic [19]. With the availability of historic process data from information systems in form of event logs and the rise of process mining techniques in the last ten years [55], also event logs are used for resource allocation in business processes: for example, to identify data on resources [2], or to detect resource allocation rules [37]. The different types of algorithmic approaches to support the resource allocation, and the role of process models and data for them will be analyzed in this study.

## 3 RELATED WORK

In this section, existing BPM surveys and surveys on resource allocation in business processes are presented and discussed. A first comprehensive study on use and representation of (mostly) human resources in the existing BPMSs was given by Russel et al. [46] in 2005. The resource patterns, which were structurally collected from different process modeling languages and BPMSs, are heuristics focusing on individual process cases. They are greedy solutions that may become sub-optimal for a set of running process instances, especially when process cases have different priorities.

In a comprehensive survey on BPM, based on the conference proceedings of the International Business Process Management Conference and books published in this community, van Aalst [53] provides typical BPM use cases in which resources and their allocation do not play a central role. Still, it is mentioned that resource information can be discovered from event logs and enhanced models, that workflow engines have to handle resources, and that papers were observed, which deal with optimal resource allocations.

Cabanillas [8] presents research works on resource handling in process- and resource-oriented systems, categorized into: (1) resource assignment (i.e., the definition of resource requirements for process activities at design time), (2) resource allocation (i.e., designation of concrete resources to a specific task during runtime) and (3) resource analysis (i.e., evaluation of process execution with the focus on resources).

In the resource allocation part, only a small set of research studies are presented as the author did not intent to present an exhaustive literature review, but rather, a framework with representative works.

Arias et al. [3] provides a systematic mapping study on human resource allocation in business process management and process mining with several limitations. The focus is only human resources and the mapping study focuses on insights where and when the study was published, but not discussing their solved problems etc. Further, it is limited to studies to which the authors could access at their university.

A survey on automated planning and BPM [39] shows that artificial intelligence can leverage certain challenges in business process management, such as the automatic generation of process models, allow process adaptations or run conformance checking. It gives a concrete method for building planning problems. Although resources play an indirect role, resource allocation is not discussed as an application area.

Based on the related work, we can observe that a comprehensive analysis of the research works in context of resource allocation in business processes is missing. So far no systematic review exists that represents the goals, capabilities, solution techniques, and maturity of existing resource allocation approaches and compares them in a structured way.

## 4 RESEARCH METHOD

A Systematic Literature Research (SLR) [33, 40] allows to identify and analyze relevant and existing literature related to a specific research question, while aiming to minimize bias and maximize reproducibility. Thus, in this paper, we apply an SLR methodology to provide a fundamental understanding of approaches supporting automatic resource allocation in business processes and a categorization of those. The research method for this SLR follows the methodology from Kitchenham [33].

This section describes the search protocol followed in the SLR. First, the addressed research questions are presented in Section 4.1. The data sources and the search strings for the primary search, the backward and forward search, and the relevance checks are described in Section 4.2. The resulting studies were read and relevant information extracted according to a predefined data scheme, which is also given in Section 4.2.

### 4.1 Research Questions

The goal of this study is to answer the main question *"What is the state-of-the-art of automatic approaches supporting resource allocation in business processes?"*. Therefore we divided this general question into four more concrete sub-questions to investigate and describe the existing research:

RQ1 *What are the targeted resource allocation goals and capabilities?* Usually, a resource allocation targets an optimization goal, e.g. minimizing the flow time, applicable in different use cases. In response to this RQ, we aimed at generating an overview on the different resource allocation goals and the resource allocation capabilities of the approaches: which of the approaches support traditional 1-to-1 mappings, and what else is supported?

RQ2 *What is the role of process models and process data (in form of event logs) in the resource allocation approach?* Resource allocation in business processes is special because the order of process activities needs to be considered [71]. We want to understand the role of process models or process data (often in form of event logs) used by the resource allocation approaches for business processes and what kind of information is used by them as inpt.

RQ3 *Which input data are used by the different approaches supporting the resource allocation in business processes?* Arias et al. [1] derived a taxonomy of resource attributes, which were used as input for resource allocation approaches for business processes. When addressing this research question, we plan to reuse this taxonomy as basis to understand and classify the input data used in the identified studies. Furthermore, we plan not only to analyse the used resource attributes but also the task attributes necessary for a resource allocation approach.

RQ4 *Which solution strategies are used and are the approaches following a local or global optimization?* With this research question, we want to get an understanding of the types of solution approaches that are used for the resource allocation, such as rules, heuristics, genetic algorithms, etc. We want to analyze whether techniques from other disciplines were used and how they had to be transformed in order to be applicable for business

Table 2. Database, search queries, and resulting number of studies in the primary search. TS of Web of Science can be used for searches for topic terms within a record, such as search in abstract, author keywords, etc.

| Database | Search queries | Number |
|---|---|---|
| ACM Digital Library | recordAbstract:(resource staff task) + (allocation assignment scheduling optimization planning) + ("business processes" "process mining") | 535 |
| IEEEXplore | ((task OR staff OR resource) AND (allocation OR assignment OR scheduling OR optimization OR planning) AND ("process mining" OR "business processes")) | 1086 |
| Science Direct | (resource OR staff OR task) AND (allocation OR assignment OR scheduling OR optimization OR planning) AND ("process mining" OR "business process management") | 61 |
| Web of Science | (TS=(task OR staff OR resource) AND (allocation OR assignment OR scheduling OR optimization OR planning) AND ("process mining" OR "business processes")) AND LANGUAGE: (English) | 722 |

processes. Furthermore, we want to investigate whether approaches simply follow a local optimization where the focus is only on single process cases, or a global optimization, where the set of to-be executed process tasks is considered, possibly with different level of importance.

RQ5 *How mature are the proposed resource allocation approaches in terms of applicability and the availability of an implementation and their evaluation?* Depending on the maturity level of a research approach, its applicability in real-world settings can be inferred. When addressing this RQ, we distinguish between 4 levels (low, medium, high, advanced) and base this decision on the evaluation, the availability of a prototype/pseudocode and whether it is an approach for local or global optimization. Approaches which have neither been implemented nor evaluated are categorized as *low*. Only approaches which (i) target a global optimization in the resource allocation, (ii) have been implemented or at least specified with pseudocode, and (iii) have been properly evaluated, are classified as *high* or more; all others as *medium*. The subset of approaches fulfilling the criteria for *high*, which further provide an accessible research prototype, are categorized as having *advanced* maturity.

### 4.2 Search for studies and data extraction

Our search for studies was split into two phases: a primary search and a secondary search. In the primary search, research databases were queried with a predefined set of search terms concerning the abstract, title and keywords. The resulting set of studies was reviewed to identify a core set of actual relevant studies. This core set was then used to conduct a backward and forward search to find additional relevant studies in order to maximize the completeness of the search. The complete search process, with the resulting number of studies, is illustrated as a BPMN process diagram in Figure 3, and described in more detail below.

In the primary search, we queried several research databases: ACM Digital Library, IEEE Xplore, SciVerse Scopus, and Web of Science, with the following general search term: (RESOURCE OR TASK) x ALLOCATION x (BUSINESS PROCESS OR PROCESS MINING). The search was conducted in June 2019. In some preceding searches, we have observed that the defined search led to an enormous set of resulting studies. This set included a high proportion of short conference papers. Thus, we decided to focus on journal papers, which are usually more detailed and of higher quality, and filtered for such articles at those databases (where possible). We are aware that also high quality works are published in conferences, which we plan to include in the backward and forward search. The exact search queries per database including synonyms, and the resulting number of studies are shown in Table 2.

The resulting 2,419 studies were, with the help of the literature manager tool Citavi, checked for duplicates, and non-journal publications were filtered out. Some duplicates needed to be removed manually in an additional step. The remaining 766 studies were checked independently by two authors of this paper for their relevance, based on title and abstract and with the help of the following inclusion and exclusion criteria:

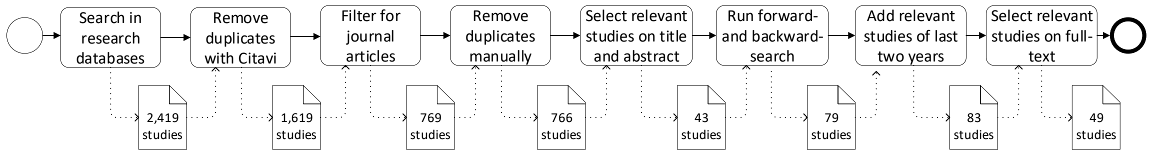



Fig. 3. Search process and the number of studies as result of the difference steps.

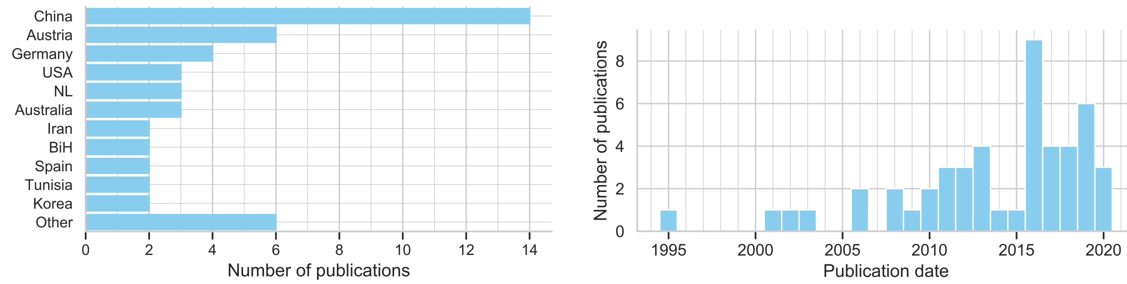
IN1 The study describes an algorithm or technique to support resource allocation in the context of business processes.
EX1 The study provides exclusively a survey on topics related to resources or business processes.
EX2 The study is not written in English.
EX3 The study is not published in a peer-reviewed journal.
EX3 The study focuses only on modeling resources or resource analysis.
EX4 The study focuses only on scheduling/planning of activities.
EX5 The study focuses on the design, configuration, or application of an ERP system.
EX6 The study only describes a resource allocation approach for one specific use case.
EX7 The study describes an approach for allocating complete business process instances for their execution in an execution environment, such that a process instance is considered as an entire block and not as a set of related tasks (for instance, some studies on executing process instances in the cloud, like [57]).

All studies which were categorized by both authors as relevant were accepted. Those studies for which a disagreement existed were discussed and a final decision was jointly made. The resulting core set of relevant studies, comprising 43 papers, was then used for backward and forward search to find additional studies. Thereby, we also considered conference or workshop papers in the backward search because we assumed that these studies which referenced by a journal article have a high implication on the research field. For this step, Web of Science was used. Identified papers were immediately checked for their relevance. Studies for which a researcher was not sure were discussed with the co-authors. Relevant papers were added to the core set of relevant studies, which resulted in 79 studies.

As we have run the first search in June 2019, we updated the set of relevant studies by rerunning the searches in the research databases in February 2021 and selected relevant studies manually from the databases. We found four additionally studies. Next, we read the full-text of the 83 studies and excluded another 34 studies, because they did not fulfill the inclusion and exclusion criteria. Each exclusion decision was discussed with the group of co-authors. Reasons were often that the focus was rather on process modeling or resource analysis, the presented resource allocation approach was too domain-specific, or that the work has been published in different types of papers, whereby always the most extensive versions have been kept. The final set of 49 studies were read completely and relevant information were extracted according to the following predefined data scheme[2]:

- Year, Country
- Allocation capability (1-to-1, 1-to-m, m-to-1, m-to-n)
- Resource type (active vs. passive)
- Local vs. global optimization
- Allocation goal and constraints
- Task and resource attributes

[2]The accepted and not accepted studies as well as the result from the data extraction can be found in the following spreadsheet: https://drive.google.com/file/d/1AnTrFm0olWPzKnMU1iCRMX26z_gvAIje/view?usp=sharing. After acceptance, we plan to publish the data on the *figshare* platform.




(a) Originating country

(b) Publishing year

Fig. 4. Resulting studies categorized by the originating country (corresponding author and the published year).

- Usage of process model/data
- Solution technique
- Type of evaluation (none, simulation experiments, experiments with real-world data, case study etc.)
- Prototype (available, only pseudocode, etc.)

## 5 RESOURCE ALLOCATION APPROACHES IN BUSINESS PROCESSES

In this section, we present the results of the SLR structured by the research questions. However, before we do so, we present basic statistics about the final set of 49 primary studies. Then, the resource allocation types, and the targeted optimization goals of the approaches are presented in Section 5.1, addressing RQ1. Next, the role of process models and process data in the resource allocation approaches is discussed in Section 5.2, addressing RQ2. The needed attributes on the tasks and resources as input are presented as taxonomies in Section 5.3, addressing RQ3. Solution approaches are discussed in Section 5.4, addressing RQ4. Finally, the evaluation techniques, the usage of research prototypes, as well as the maturity level of the approaches are presented in Section 5.5, addressing RQ5.

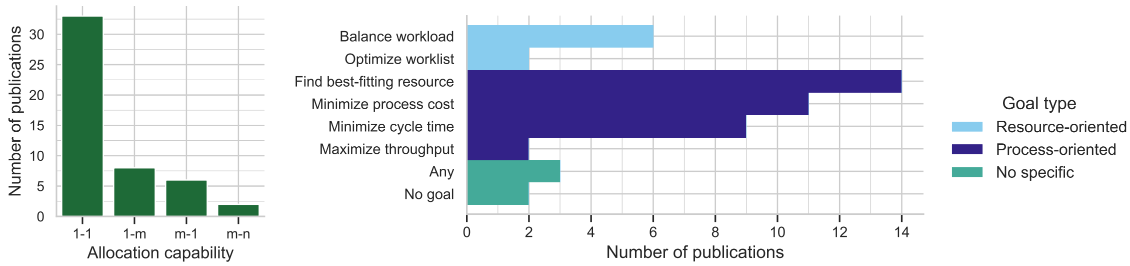
Around 30% of the primary studies analyzed in this SLR on resource allocation in business processes originate from China (14 studies) as shown in Figure 4a, followed by Austria (6 studies) and Germany (4 studies). Next to Asia and Europe, a global interest in this topic can be observed: works by authors from North (USA (3 studies) and South America (Chile (1 study)), from Africa (Tunisia (2 studies)), and from Australia (3 studies) were also found. The first work of our study collection was published in 1995, followed by some studies published after 2000 and onward (see Figure 4b). After 2010, more published studies on resource allocation in processes can be observed with a peak in 2016. A majority of papers studied in this review have been published in the last 5 years.

### 5.1 RQ1: Resource allocation types and optimization goals

In this subsection, we explore *RQ1: What are the targeted resource allocation goals and capabilities?* To do so, we investigate the resource allocation capabilities supported in literature, followed by the used allocation principles (i.e., pull vs. push). Furthermore, the targeted optimization goals are categorized and presented.

Figure 5a shows how many studies support the different resource allocation capabilities. Thereby, four resource allocation capabilities can be differentiated (relations as |tasks|-to-|resources|):

- 1-to-1 allocation, where one resource is assigned to exactly one task;




(a) Supported allocation capabilities

(b) Optimization goals for allocation

Fig. 5. Support allocation capabilities and optimization goals of the studies.

- many-to-1 allocation, where the capacity of a resource is greater one, and several tasks can be assigned to it;
- 1-to-many allocation, where a team of resources is assigned to a task to solve it; and
- many-to-many allocation, where a team of resources is assigned to a set of tasks.

The concrete studies supporting a certain capability are given in Table 3. Most studies support an assignment of one resource to one task. Eight studies support the 1-to-many allocations where one task is assigned to multiple resources. Some of these studies simply consider the possibility of having more than one resource assigned to a task, and the assigned resources self-select which one completes the task. In contrast, others support the creation of (possibly high-performing) teams for a task [34, 69]. Furthermore, six studies consider that resources can have capacities greater than one, or that it is better for resources to work on similar or related tasks in sequence, and in either case support many-to-1 allocations where multiple tasks are allocated to one resource. Finally, two studies also allow many-to-many allocations where an arbitrary set of tasks can be assigned to an arbitrary set of resources.

A majority of the identified resource allocation approaches follow a *push*-principle as shown in Table 3, where tasks are allocated to resources with the assumption that a resource works on this task as soon as it is available. Seven studies follow the *pull*-principle, whereby tasks are added to a worklist of the resource. The resource can then decide how to organize the tasks on their worklist. For example, Barba et al. [4] focus on resource allocation in knowledge-intensive processes and provide knowledge workers a prioritization of tasks, on which to work first, but the workers are still free to choose. Three studies support both principles, such that one of the two principles can be selected and implemented in the process execution environment.

Many studies follow a specific optimization goal in their resource allocation. It can be observed that a majority focuses on goals around improving the performance of the process, and smaller portion of studies focuses on improving the performance of the resources as given in Figure 5b. Some few studies have no (specific) optimization goal. In the following, we discuss these categories in more depth:

- **Process-oriented optimization.** A majority of the identified studies aims at *finding the best-fitting resource*. In case of the best-fitting resource, a resource allocation tries to identify the best match between tasks and resources based on the needs of a task and the characteristics of the resources. Half of the studies following this goal are focused on the individual case – local optimization – whereas the other half also considers the different priorities of cases – global optimization. As shown in the diagram of Figure 5b, the second-most frequent optimization goal is to *minimize the process costs*, followed by the goal to *minimize the cycle time* of process executions. A smaller portion of studies aims at *maximizing the throughput*.

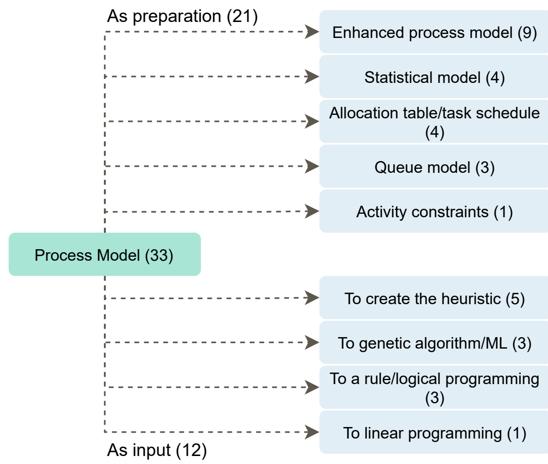
- **Resource-oriented optimization.** Most studies focusing on a resource-oriented optimization try to *balance the workload* between resources (6 studies), i.e., tasks are distributed equally to the available resources. In contrast to finding the best-fitting resource, tasks might also be allocated to less suitable resources, in order to keep the workloads balanced. Two studies aim at *optimizing the worklist*: one study focuses on prioritizing tasks [4], and the other on minimizing the entropy of worklists [66], which means that rather similar tasks are allocated to a resource.
- **No explicit optimization goal.** Three studies support the idea that the optimization goal can be individually defined when applying and implementing the resource allocation approach. Huang et al. [29] maximize the allocation reward, and the calculation of the reward can be specified by the user. Whereas Duran et al. [18] only describe that a multi-objective optimization problem has to be defined for a resource allocation, Ihde et al. [30] provide a way to define the optimization goal individually for each process activity at design-time. Two studies working with resource allocation rules [7, 25] are not associated with a specific resource allocation goal.

### 5.2 RQ2: Role of process models and data

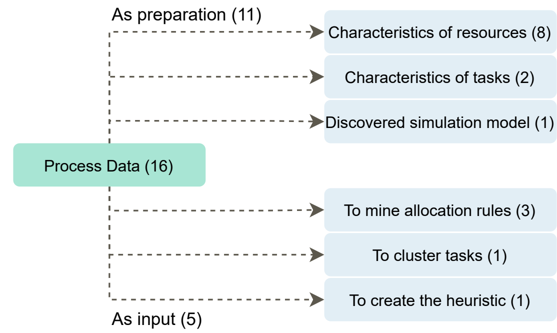
We now turn to investigating *RQ2: What is the role of process models and process data in the resource allocation approach?* When analyzing the role of process models and data, it can be observed that most of the primary studies (33 studies) use process models for the resource allocation, and fewer (16 studies) use process data in form of event logs. We summarize our results in Figure 6. We further categorized the studies into those which use process models/data for preparing specific input for their approach, and those which apply it as input directly.

| Reference | Year | Country | Capability | Principle | Optimization Goal | PM/PD | Role | Type | Solution technique | Evaluation | Prototype | Maturity |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bussler & Jablonski [7] | 1995 | Germany | many-to-1 | Pull | No goal | PM | Prep. | local | Rule | No evaluation | not acc., pseudoc. | medium |
| Van Hee et al. [56] | 2001 | NL | many-to-many | Push | Minimize cycle time | PM | Input | local | Linear programming | Toy example | no | low |
| Kumar et al. [35] | 2002 | NL | 1-to-1 | Pull | Find best-fitting resource | PM | Prep. | local | Rule | Toy example | no | low |
| Eder et al. [19] | 2003 | Austria | 1-to-1 | Pull | Balance workload | PM | Prep. | global | Heuristic | No evaluation | no | low |
| Doerner et al. [16] | 2006 | Austria | 1-to-1 | Push | Minimize process cost | PM | Input | global | Heuristic | Case study | pseudocode | high |
| Ha et al. [21] | 2006 | Korea | 1-to-1 | Push | Balance workload | PM | Prep. | global | Rule | (Comp.) sim. experiments | pseudocode | high |
| Rhee et al. [45] | 2008 | USA | many-to-1 | Push | Balance workload | PM | Input | global | Heuristic | (Comp.) sim. experiments | not acc., pseudoc. | high |
| Zhou et al. [72] | 2008 | China | 1-to-1 | Push | Minimize process cost | PM | Prep. | global | Genetic algorithm | Toy example | no | low |
| Xu et al. [62] | 2009 | Australia | 1-to-many | Push | Minimize process cost | PM | Input | global | Rule | (Comp.) sim. experiments | pseudocode | high |
| Delias et al. [12] | 2010 | Greece | 1-to-1 | Push | Balance workload | PM | Prep. | global | Discrete approx. | (Comp.) sim. experiments | not accessible | medium |
| Huang et al. [28] | 2010 | China | 1-to-1 | both | Any | PM | Input | local | Machine Learning | (Comp.) experiments | available | medium |
| Kamrani et al. [32] | 2011 | Schweden | 1-to-many | Push | Minimize process cost | PM | Input | global | Heuristic | (Comp.) sim. experiments | pseudocode | high |
| Huang et al. [25] | 2011 | China | 1-to-1 | Push | No goal | PD | Input | local | Trained rule | Experiments + Case study | not acc., pseudoc. | medium |
| Huang et al. [29] | 2011 | China | 1-to-1 | Push | Minimize process cost | PM | Prep. | global | Machine Learning | (Comp.) experiments | available | advanced |
| Huang et al. [27] | 2012 | China | 1-to-1 | Push | Minimize process cost | PM | Prep. | global | Genetic algorithm | (Comp.) sim. experiments | not acc., pseudoc. | high |
| Huang et al. [26] | 2012 | China | 1-to-1 | Pull | Find best-fitting resource | PD | Prep. | local | Rule | Case study | available | medium |
| Liu et al. [37] | 2012 | China | 1-to-1 | Push | Find best-fitting resource | PD | Input | global | Trained rule | (Comp.) experiments | not acc., pseudoc. | high |
| Barba et al. [4] | 2013 | Spain | 1-to-1 | Pull | Prioritize tasks | PM | Prep. | local | logic programming | (Comp.) sim. experiments | not acc., pseudoc. | medium |
| Xu et al. [63] | 2013 | Australia | 1-to-1 | Push | Minimize cycle time | PM | Prep. | global | Rule | (Comp.) sim. experiments | not acc., pseudoc. | high |
| Cabanillas et al. [9] | 2013 | Austria | 1-to-1 | Push | Find best-fitting resource | PM | Input | local | Heuristic | No evaluation | available | medium |
| Kumar et al. [34] | 2013 | USA | 1-to-many | Push | Find best-fitting resource | PD | Prep. | global | Heuristic | Case study | not acc., pseudoc. | high |
| Schall et al. [47] | 2014 | Austria | many-to-many | Push | Find best-fitting resource | PM | Prep. | local | Rule | (Comp.) sim. experiments | not acc., pseudoc. | medium |
| Zhao et al. [70] | 2015 | China | 1-to-1 | Push | Minimize cycle time | PD | Prep. | local | Machine Learning | (Comp.) experiments | not accessible | medium |
| Pflug et al. [43] | 2016 | Austria | many-to-1 | Push | Maximize throughput | PD | Input | global | Machine Learning | Case study | not acc., pseudoc. | high |
| Schoenig et al. [50] | 2016 | Germany | 1-to-1 | Push | Minimize cycle time | PD | Input | global | Trained rule | (Comp.) sim. experiments | not accessible | medium |
| Wibisono et al. [59] | 2016 | Indonesia | 1-to-1 | Push | Minimize cycle time | PM | Prep. | local | Rule | (Comp.) sim. experiments | pseudocode | medium |
| Xie et al. [61] | 2016 | China | 1-to-many | Push | Minimize cycle time | PM | Prep. | global | Heuristic | Experiments + Case study | available | advanced |
| Xu et al. [64] | 2016 | Australia | many-to-1 | Push | Maximize workload | PM | Prep. | global | Genetic algorithm | (Comp.) sim. experiments | not acc., pseudoc. | high |
| Zhao et al. [68] | 2016 | China | 1-to-1 | Push | Find best-fitting resource | PD | Input | global | Heuristic | (Comp.) experiments | pseudocode | high |
| Havur et al. [22] | 2016 | Austria | 1-to-1 | Push | Minimize cycle time | PM | Input | global | logic programming | (Comp.) sim. experiments | no | medium |
| Djedovic et al. [15] | 2016 | BiH | 1-to-many | Push | Minimize process cost | PM | Prep. | global | Genetic algorithm | Case study | not accessible | medium |
| Yaghoubi et al. [66] | 2016 | Iran | 1-to-1 | Push | Minimize worklist entropy | PD | Prep. | global | Machine Learning | (Comp.) experiments | not accessible | medium |
| Hirsch et al. [24] | 2017 | USA | 1-to-1 | Push | Minimize cycle time | PM | Prep. | global | Linear programming | (Comp.) sim. experiments | not acc., pseudoc. | high |
| Yaghoubi et al. [65] | 2017 | Iran | many-to-1 | Pull | Balance workload | PM | Prep. | global | Rule | (Comp.) experiments | pseudocode | high |
| Zhao et al. [71] | 2017 | China | 1-to-1 | Push | Minimize cycle time | PM | Input | global | Heuristic | (Comp.) experiments | not accessible | medium |
| Farah Bellaaj et al. [5] | 2017 | Tunisia | 1-to-1 | Push | Find best-fitting resource | PD | Prep. | local | Rule | No evaluation | not acc., pseudoc. | medium |
| Arias et al. [2] | 2018 | Chile | 1-to-1 | both | Find best-fitting resource | PD | Prep. | global | Linear programming | Experiments + Case study | available | advanced |
| Djedovic et al. [14] | 2018 | BiH | 1-to-many | Push | Minimize process cost | PD | Prep. | global | Genetic algorithm | (Comp.) sim. experiments | not accessible | medium |
| Si et al. [51] | 2018 | Macau | 1-to-1 | Push | Minimize process cost | PM | Input | local | Genetic algorithm | Case study | not acc., pseudoc. | medium |
| Erasmus et al. [20] | 2018 | NL | 1-to-1 | Push | Find best-fitting resource | PM | Input | global | Rule | Case study | not acc., pseudoc. | high |
| Lee et al. [36] | 2019 | Korea | 1-to-1 | both | Find best-fitting resource | PD | Prep. | local | Rule | Experiments + Case study | no | medium |
| Luo et al. [38] | 2019 | China | 1-to-1 | Pull | Find best-fitting resource | PD | Prep. | local | Trained rule | No evaluation | not acc., pseudoc. | medium |
| Soeffker et al. [52] | 2019 | Germany | 1-to-1 | Push | Maximize throughput | PM | Prep. | global | Heuristic | (Comp.) sim. experiments | not acc., pseudoc. | high |
| Xie et al. [60] | 2019 | China | 1-to-1 | Push | Minimize process cost | PM | Input | global | Genetic algorithm | Experiments + Case study | not acc., pseudoc. | high |
| Sven Ihde et al. [30] | 2019 | Germany | many-to-1 | Push | Any | PM | Prep. | global | Any | Case study | available | advanced |
| Duran et al. [18] | 2019 | Spain | 1-to-many | Push | Any | PM | Prep. | global | Heuristic | (Comp.) sim. experiments | available | advanced |
| Bellaaj Elloumi et al. [6] | 2020 | Tunisia | 1-to-1 | Push | Minimize process cost | PD | Prep. | local | Machine Learning | (Comp.) sim. experiments | not acc., pseudoc. | medium |
| Zhao et al. [69] | 2020 | China | 1-to-many | Push | Find best-fitting resource | PD | Prep. | local | Machine Learning | (Comp.) sim. experiments | not acc., pseudoc. | medium |
| Pereira et al. [42] | 2020 | Portugal | 1-to-1 | Push | Find best-fitting resource | PM | Prep. | local | Rule | No evaluation | no | low |

Table 3. Studies and their categorizations ordered by publication year.




(a) Role of process models




(b) Role of process data

Fig. 6. Role of process models (a) and data (b) in resource allocation approaches, categorized into approaches using the respective artifact either as direct input, or to prepare an input for their approach; and the artifacts' usages. Number of studies in a particular class are shown in parentheses.

*Process models.* Process models are mostly used to prepare an input (21 studies) for the resource allocation technique. Often, enhanced process models (9 studies) are created on the basis of a traditional process models, extended with information on the resources, the duration and the requirements of the tasks, and the arrival time of instances. Other studies aim at the creation of statistical models (4 studies), such as Bayesian models [59], a Markov decision processes [29, 52] or a Maude simulation models [18]. The latter reflects distributions in the process execution as information for the resource allocation approach. A third category prepares allocation tables [63], task schedules [12, 64], or both [19] (together 4 studies) based on the process models as information for the resource allocation. While some studies create advanced queue models (3 studies) [21, 27, 65] as basis of their resource allocation approach, Hirsch et al. [24] simply use the constraints between the activities defined in the process model.
As direct input (12 studies), traditional process models are used to create heuristics (5 studies) [9, 16, 32, 45, 70] for the resource allocation, or for genetic or machine learning (ML) algorithms (3 studies) [28, 51, 60]. We discuss the concrete solution techniques in Section 5.4 in detail. Some studies use the process models as input to create rules or for logic programming (3 studies) [20, 22, 62], and one study also uses the model as input for linear programming [56].

*Process data.* Process data is used for resource allocation in 16 studies. Eleven primary studies use them for preparation and five of them as input to the resource allocation technique directly. Eight out of the eleven studies in the former class employ the process data to identify some insights on resources of the process (i.e., characteristics of resources), e.g., their previous performance [2, 26, 36, 70], their expertise [2, 5, 38], their workload [2, 5, 70], their team compatibility [34], or their social context [36]. Other studies identify characteristics of tasks during preparation for resource allocation, such as similarity between tasks [66] or misallocations of tasks in the past [6]. Djedovic et al. [14] discover a process simulation model from the event log, which is then used as input.
As direct input, process data is used by some studies to mine rules for the allocation (3 studies) [25, 37, 49]. Pflug et

al. [43] use an event log to cluster similar tasks so that they can jointly be allocated to a resource, and Zhao et al. [68] to create a resource allocation heuristic.

### 5.3 RQ3: Resource and task attributes

In this subsection, we investigate *RQ3 Which input data are used for resource allocation in business processes?* In a resource allocation, characteristics of both the tasks and resources can be considered to identify a fitting match. These characteristics are often encoded as task and resource attributes. Contrary to a previous study [1], we consider resource and task attributes separately.

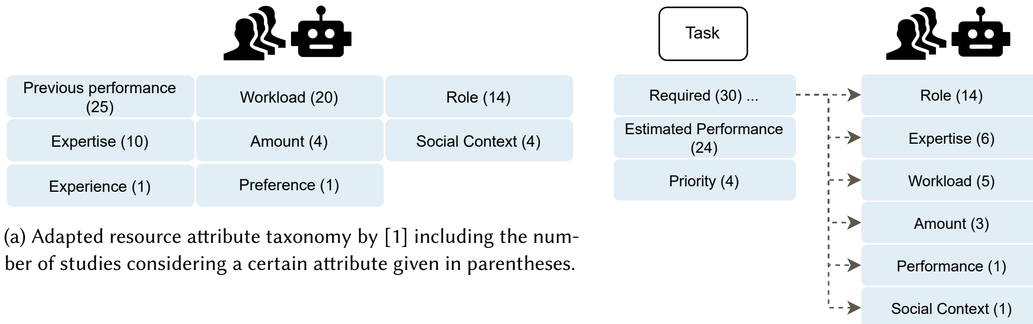
*5.3.1 Resource attributes.* Arias et al. [1] provide a taxonomy for human resource allocation criteria based on an SLR conducted in [3]. We adopt this taxonomy to classify the resource attributes discussed in the identified primary studies. As Arias et al. [1] focus on human resources we had to extend the generality of the aforementioned categories to also include non-human resources. However, we found that most studies (40 studies) focus on human resources, while only nine studies [5, 16, 25, 28–30, 61, 71, 72] focus on resources in general.

The result of this classification is visualized in Figure 7a, showing the different categories of attributes as well as how often they are used in the studies. In the following, the different categories are briefly described.

- **Previous performance** describes all performance attributes that are based on the execution history of the resource. This can be, for example, the cost, quality or execution time of previous executions of the resource;
- **Workload** of a resource describes attributes that are based on the schedule of a resource. This includes attributes such as availability, allocation or idle level;
- **Role** describes attributes pertaining to the role of a resource, such as authorizations, organisational position or responsibilities;
- **Expertise** includes attributes encoding a resource's capabilities, skills and knowledge. This includes functional attributes which are associated with the resource directly, such as adaptability, but also non-functional attributes which may include environmental factors and employed aids. It also includes attributes based on work variety, i.e., the analysis of similar and dissimilar tasks in the execution history of a resource;
- **Amount** comprises attributes encoding the number of resources that exist. For passive resources this may encode the amount of resources in stock, for active resources this may encode the number of resources of a specific type;
- **Social context** encodes attributes based on the social network of a resource. These attributes may measure the ability to collaborate or the overall compatibility of resources, but also more abstract social constructs such as the social position or influence of a resource within its network;
- **Experience** encodes attributes such as years of service or other quantifiable attributes based on the experience of a resource. Note the difference to expertise, where we asses the actual ability of a resource;
- **Preference** contains attributes expressing the preference of a resource executing certain tasks.

We were able to categorize all attributes, even for non-human resources, using the presented taxonomy without introducing any new categories. Contrary to [1], we did not observe any study considering *trustworthiness* (a level of trust a resource may have to perform a task) as a resource attribute. Accordingly, we omit this notion from our taxonomy for resource attributes.

We found that most studies (25 studies) [2, 5, 6, 14, 18, 22, 25–29, 34, 36, 37, 45, 56, 59, 60, 63, 66, 68–72] consider attributes from the category previous performance. Notably, most studies consider cost (12 studies) [2, 5, 6, 14, 18, 26, 27,




(a) Adapted resource attribute taxonomy by [1] including the number of studies considering a certain attribute given in parentheses.

(b) Task attribute taxonomy including the number of studies considering a certain attribute in parentheses. Note: “Required ...” gives the total sum (30) of all requiring resource attributes.

Fig. 7. Taxonomies of used task and resource attributes in the resource allocation.

29, 60, 63, 71, 72] and time (4 studies) [5, 22, 56, 63] as performance criteria. Twenty studies consider workload [2, 4, 5, 18, 19, 21, 26, 27, 34, 35, 43, 45, 52, 62, 64–66, 68, 70, 72]. For workload, availability of a resource is considered most often (10 studies) [4, 26, 27, 34, 35, 43, 52, 64, 68, 72]. Fourteen studies consider the role attribute [5, 7, 12, 15, 22, 24, 34, 35, 50, 59, 62, 63, 65, 69]. We found that the role is most often encoded directly as an attribute (9 studies) [5, 7, 15, 22, 24, 35, 50, 62, 63]. Ten studies consider attributes belonging to the expertise category [2, 15, 28, 32, 38, 42, 47, 63, 68, 69]. We found that amount [16, 51, 60, 61] and social context [34, 36, 47, 69] are considered less often (4 studies each). Experience is considered only by Zhao et al. [69] and preference only by Huang et al. [28]. Five studies take a more flexible approach and are able to consider any quantifiable attribute [7, 9, 16, 20, 30]. This, for example, can be achieved as in Doerner et al. [16], by defining a custom cost function, or, as in Ihde et al. [30], by defining allocation algorithms based on the task to be allocated. Notably, only Doerner et al. [16] considers both active and passive resources, while all other studies consider active resources only.

*5.3.2 Task attributes.* Task attributes often encode the requirements a resource has to satisfy. These requirements can be mapped onto our previously presented taxonomy for resource attributes. For example, a task may require a resource with a certain past performance, such as requiring a certain level of quality or time in which the task can be performed. The identified taxonomy for task attributes can be found in Figure 7b. Note that an arrow indicates the aforementioned mapping of a task requirement. We also provide the amount of studies that use the corresponding category in the figure. “Required...” gives the total sum of studies considering task requirements, and the corresponding categories are discussed below. Additionally, we identified attributes influencing allocation decisions in a more indirect manner. We categorize them as follows.

- **Estimated performance** describes performance attributes such as duration or cost which are estimated for a task;
- **Priority** contains attributes assessing the priority of a task. Priority may be encoded via a deadline or a simple scale indicating the importance of a task.

In total, 30 studies encode some **requirement** as task attribute. Most studies require the resource to have a specific role (14 studies) [5, 6, 9, 15, 21, 24, 27, 35, 42, 45, 47, 62, 63, 69], a certain expertise (6 studies) [20, 32, 34, 38, 42, 47], or certain workload (5 studies) [19, 30, 45, 59, 65]. Only three studies consider an amount [14, 15, 32]. Schall et al. [47] requires a performance attribute and Yaghoubi and Zahedi [66] requires a social context attribute. 24 studies consider the estimated performance of a task [4, 6, 12, 16, 18, 21, 22, 25, 26, 32, 34, 37, 45, 50, 51, 56, 59, 61, 63, 65, 68, 70–72]. Of these, most studies (19) consider the duration of a task [4, 6, 12, 16, 18, 21, 22, 25, 26, 32, 45, 51, 56, 59, 61, 63, 65, 68, 72]. Only four studies consider the priority of a task [14, 30, 35, 68]. While we found one study that considered experience [69] and one that considered the preference [28] of a resource, we did not find any study in which a task would require an experience or preference attribute for allocation. We, therefore, omit experience and preference from our task taxonomy in Figure 7b.

### 5.4 RQ4: Solution techniques

Resource allocation is typically viewed as an optimization problem. In the following, we investigate *RQ4: Which solution strategies are used and are the approaches following a local or global optimization?* In the primary studies, we could identify different types of solution techniques for solving the optimization problem, depending also on the way how the problem was modeled. In this section, the different identified types of solution techniques are presented. We categorize them by their execution effort and time vs. their solution quality, and by the individualization options of the approaches, as explained next.

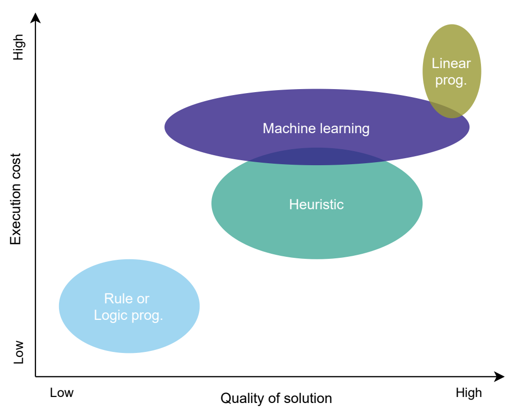



Fig. 8. Identified solution strategies for resource allocation in business processes and an approximate categorization regarding their execution cost and solution quality in the average case

When deciding for a solution strategy, it is important to balance the effort and the time that is needed to generate a fitting solution with the quality of the resulting solution [11]. Solution techniques that focus primarily on the quality of the result tend to have much higher execution cost (i.e., effort and time). The most prominent representative of these techniques are linear programming approaches as shown in Figure 8. This figure was created to provide an approximated categorization of solution techniques and their execution cost and quality of solution as it can be observed in the average case. On the other end of the spectrum are solution techniques, such as rules and logic programming, which focus on minimizing the execution cost in exchange for not finding the best solution in all cases. These techniques are used preferably in urgent scenarios, when finding any solution is enough. Heuristics are found in the middle of this spectrum as visualized in Figure 8. Most of the time they can result in a higher minimum amount of quality of the solution in contrast to rule-based approaches [22], while only having a slightly higher execution cost.

A further differentiation we observed is the decision to use a general or individualized algorithm. Whereas general solution techniques are defined beforehand and are used in every allocation from then on, individualized algorithms try to find a solution technique that adapts to one scenario of resource allocation individually. In order to create individualized techniques, machine learning methods are used, such as genetic algorithms. As shown in Figure 8, such approaches can also delivery a high solution quality, but that is very dependent on the training data used.

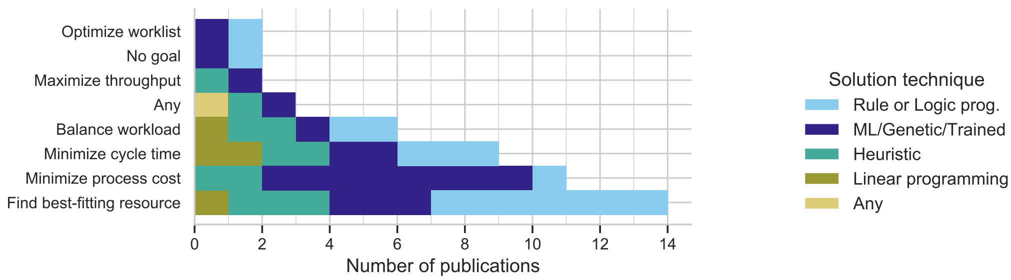



Fig. 9. Found solution techniques grouped by their allocation goal

In Figure 9, the different solution techniques of the aforementioned categories grouped by their allocation goals are shown. Additionally, one primary study by Ihde et al. [30] provides an approach where any solution technique can be used. In the following, we present the solution approaches in more detail starting with techniques with a lower execution cost and quality – rules and logic programming, which were mostly found in the primary studies. Then, used heuristics are presented followed by approaches using linear programming. Finally, the individualized approaches are presented, where machine learning is used to develop rules as well as heuristics trained from historic data. Finally, we present, on a higher abstraction level, which solution techniques support local optimization and which of them global optimization.

*5.4.1 Rules & logic Programming*. The first category of solution techniques focuses on minimizing the effort and time to find a suitable solution with the disadvantage to have lower results quality-wise in comparison to the types of solution techniques. A majority of the primary studies (15 studies) proposed such an approach. Traditionally, in Business Process Management the use of rules is wide-spread [46]. In our set of studies a total of 13 studies considered rule-based approaches. These studies use rules in two kind of ways:

- as simple constraints for a machine (10 studies) [5, 21, 26, 36, 42, 47, 59, 62, 63, 65],
- as human readable guidelines (3 studies) [7, 20, 35] to decide on allocations.

We also decided to group logic programming approaches together with rules, as logic programming defines constraints for machine execution, which are later used for BPMSs to execute processes. Therefore, logic programming approaches heavily resembles rule-based approaches. Moreover, with only two studies being classified as logic programming [4, 22] they only represent a minority.

As shown in Figure 9, rule-based approaches mostly concentrate on finding the best-fitting resource for a task [5, 20, 26, 35, 36, 42, 47]. Furthermore, rule-based approaches support minimizing the cycle time of processes [22, 59, 63] , balancing the workload [21, 65], minimizing the process cost [62], or prioritizing tasks [4]. A special case here is the paper by Bussler and Jablonski [7]. Their approach does not try to fulfill a specific goal, but instead introduces a more generic approach that allows creating customized goals depending on the use case.

*5.4.2 Heuristics.* Heuristics, the subjects of the second identified group, try to minimize the chance to end up with only a locally best solution. Therefore, they tend to generate higher quality solutions than rule-based approaches. However, they need more computational effort and time to produce a solution. Because of their capability of balancing execution effort with solution quality, heuristics count as a best practice for most problem-solving strategies.
Out of the 49 studies, 11 papers proposed a heuristics-based approach to solve the resource allocation problem. The most common goal is to find the best-fitting resource for a task (3 studies) [9, 34, 68]. Other process-oriented goal types are also represented as given in Table 3. For example, minimizing process cost [16, 32] , minimizing the cycle time [61, 71] or maximizing the throughput of a process [52]. On the other hand, resource-oriented goals were the focus of only two papers that try to balance the workload of a resource across multiple processes [19, 45]. Special cases are the works by Durán et al. [18] and by Ihde et al.. [30]. Durán et al.'s approach uses a generic solution that can be redefined for any goal depending on the use case, where as the approach by Ihde et al. allows to flexibly define the algorithm and their goals for each activity individually.

*5.4.3 Linear Programming.* The third group, linear programming, is based on a purely mathematical model, which results in rather complex solution techniques. Firstly, the goals and the constraints are formulated as linear function. At runtime, every possible solution is evaluated and compared to find the best solution. This guarantees a more optimal solution in contrast to the aforementioned approaches. The drawback is that evaluating every possible solution comes with high computational times. Four studies used linear programming: Two of them focused on minimizing the cycle time of processes [24, 56], whereas another work looks into another process-oriented goal, namely searching for the best-fitting resource for a task [2]. The last work researched an algorithm that balances the workload of resource, thus being resource-oriented [12].

*5.4.4 Machine Learning for developing rules and heuristics.* The previously presented techniques have in common that they are created once and cannot be changed during runtime, thus resulting in a rather static behaviour. The last group of approaches uses solution techniques that are individually created or adapted to certain use cases. Therefore, they tend to result in a higher quality allocations. However, this comes with the disadvantage of having to train the algorithm, which comes with its cost. This also means these approaches have two weaknesses: (i) the dependence on the quality of the training set, and (ii) whenever a change occurs in the setting (i.e., new resource gets added, processes change, etc.) the algorithm has to be retrained. Nevertheless, 18 studies were found that support such resource allocation individualized for a use case.

These dynamic approaches can be further differentiated based on the learned algorithm. We identified three main types: trained rules, genetic algorithms and machine learning.

- *Trained rules*: Four papers used their adaptive approach to define rules. The goal of finding the best-fitting resource was chosen in half of the works [37, 38]. Another study focuses on minimizing the cycle time [50]. Lastly, there exists one work that has no goal but simply aims at enhancing existing resource allocation techniques with association rules [25].
- *Genetic algorithms*: Seven papers suggested approaches based on genetic algorithms. They belong to the so called *meta-heuristic approaches*, resulting in learned heuristic algorithms. Except for one work focusing on optimizing the workload of resources [64] the remaining aim at the minimization of process costs [14, 15, 27, 51, 60, 72].

- *Machine learning approaches*: The remaining seven studies used classical machine learning approaches like reinforcement learning, decision trees or clustering algorithms to learn heuristic solution techniques for resource allocation problems. In contrast to other categorizations, we observed a high diversity of optimization goals. Two works focused on minimizing the process cost [6, 29], whereas the other papers set their goal to: finding the best-fitting resource [69], maximizing the throughput [43], minimizing the cycle time [70] or reducing the entropy of worklist entries [66]. Falling outside of these goals is the work by Huang et al. [28], which introduces a more generic approach that can be adapted to any goal depending on the concrete use case.

*5.4.5 Local vs. Global optimization.* Lastly, we analyzed the scope of the solution strategies used in the studies. We categorized the approaches which only focus on a narrow scope, such as on finding the best-fitting resource for a specific process task – *local* optimization approaches. Approaches that consider all available task of a process or of an organization and their different level of importance are considered as *global* optimization.

Resource allocation in general is mostly a NP-hard problem. Therefore, a common way to handle these kind of problems is to reduce the complexity as much as possible, while still having a meaningful result. Local optimization achieves this by reducing the complexity through limiting the problem to select the best-matching resource for a specific task. This might be useful in business processes where resource are not limited or the importance between tasks is balanced. Out of the 49 studies, 18 papers chose to develop a solution technique that operates locally as shown in Table 3. Even though a local approach reduces the complexity of the problem, most studies further limit their approach by only allowing a 1-to-1 allocation between resources and tasks (with the exception of four papers [7, 47, 56, 69]). Another observation is that most of these studies have a process-oriented goal. The exception are again four papers, which either had a resource-oriented goal in optimizing worklists [4], or no specific goal [7, 25, 28].

Nevertheless, in reality the most expensive and limited resources are often shared between process tasks to make the allocations as efficient as possible. In order to handle resources shared between different business processes, a global optimization method is needed. Thus, out the 49 studies, 31 studies support a global optimization approach. Despite the higher complexity of global approaches, only 19 papers reduced the complexity by limiting the allocation to a 1-to-1 allocations between resources and tasks. In contrast to local optimization, the global approaches support a broad range of optimization goals, they target resource-oriented goals (7 studies) as well as process-oriented goals (9 studies).

### 5.5 RQ5: Maturity levels

In this subsection, we first discuss the methods applied by the studies to evaluate their approaches and the availability of research prototypes. Afterwards, the maturity of the approaches is discussed and the more mature approaches are presented in more detail. Thus, in this subjection, we investigate *RQ5: How mature are the proposed resource allocation approaches in terms of applicability and the availability of an implementation and evaluation?*

*5.5.1 Evaluation and Research Prototypes.* Based on work by Zelkowitz and Wallace [67], we have categorized the approaches into those having no evaluation, argumentation on a toy example (i.e., an assertion with regards to [67]), case study, controlled experiments, whereby we differentiated between simulation experiments with syntactic data, and experiments with real-world data, and a combination of methods (*Experiments + Case study*). The number of used evaluation methods and the availability of a research prototype is shown in Figure 10, ordered by their number of occurrences per evaluation method. Thereby, we distinguish between works having a prototype available, having no prototype provided, having only pseudocode made available, or having a prototype but it is not (publicly) accessible.

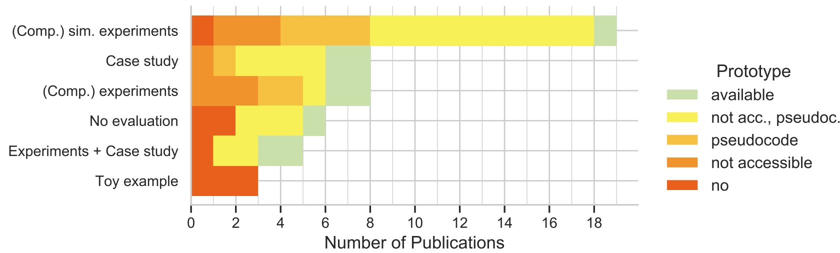



Fig. 10. Evaluation methods and the associated research prototypes per method.

In the following, we present the used evaluation methods in the order given in the previous paragraph starting from no and toy examples until the combination of methods. Surprisingly, we can observe that six studies provide no evaluation at all, and three discuss their approach on a toy example, which is rather an assertion about the functionality and usefulness of their approach. By summing up these two categories, it can be observed that 18% of the studies have not properly evaluated their approaches. Cabanillas et al. [9] is an interesting case in this category: the authors provide a Java implementation where the approach can be tested and used, but did not include an evaluation in their paper. Three other works with no evaluation discuss an implementation of their approaches but they are not publicly accessible, only pseudocode is provided.

Eight studies employ case studies to evaluate their approach. The advantages of a case study are that implications of the resource allocation approach can be studied in detail and interesting results can be found, but it is challenging to see which of the results are generalizable and which not [67]. Most of these approaches have a prototype in place to apply the approach for the selected case. However, only two prototypes are publicly accessible: Huang et al. [26] provide a plugin for the process mining toolkit ProM [31] and Ihde et al. [30] provide a stand-alone system implementation.

A majority of studies evaluate their approaches with controlled experiments (see the *[Comp.] sim. experiments* and *[Comp.] experiments* in Figure 10), whereby most of the studies use syntactic data from simulations (19 studies). Many of these simulation experiments evaluate different parameters of their approaches with regards to different settings. Five studies [14, 27, 52, 59, 64] also conduct comparative simulation experiments, in which their solution is compared to other approaches. Only Duran et al. [18] provide a prototype publicly available on a website. For the other 18 studies in this category, no prototype is accessible, but most of them provide pseudocode enabling an individual implementation (14 studies).

Experiments with real-world data have been conducted by seven studies. This type of evaluation has the advantage that it acts on more realistic data and can typically provide observations and insights with a higher confidence that these would hold in practice. Five of them not only conducted experiments with their own approach but also ran the experiments with other approaches and compared the results. ProM plugins as prototypes are provided in the works of Huang et al. [28, 29]. The other studies of this category provide mostly pseudocode, but several ones make neither a prototype nor pseudocode available.

Five studies also used a combination of evaluation methods with controlled experiments and case studies (see the *Experiments + Case studies* in Figure 10) for strengthening the evaluation of their approaches. Arias et al. [2] also provide a ProM plugin and Xie et al. [61] a MathLab implementation as research prototypes.

In summary, we can observe that many studies provide no publicly available prototype, mainly pseudocode for a re-implementation is available. Some of the studies with no accessible prototype have linked to a stand-alone solution, which is not accessible anymore. Of those eight studies providing a research prototype, five research works have used public platforms, i.e., either the process mining platform ProM [2, 26, 28, 29] or the mathematical toolbox MathLab [61], to implement their resource allocation approaches, whereas the other three chose to implement stand-alone prototypes.

*5.5.2 Maturity Levels.* After having discussed the evaluation methods and prototypes, the maturity levels of the approaches are presented in the following, distinguished into four levels (low, medium, high, and advanced). As discussed in research question 5, approaches have neither been implemented nor evaluated are categorized as *low*. Only approaches which (i) target a global optimization, (ii) have been implemented or at least specified with pseudocode, and (iii) have been properly evaluated, are classified as *high* or more; all others as *medium*. The subset of approaches fulfilling the criteria for *high*, which further provide an accessible research prototype, are categorized as having *advanced* maturity. The numbers of studies falling into the different categories are shown in Figure 11.

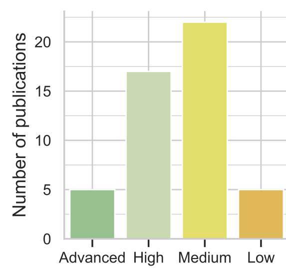



Fig. 11. Number of studies per maturity level.

Five studies provide neither a proper evaluation nor a research prototype/pseudocode. 22 studies provide at least one of the two, such that most studies are categorized as *medium*. 16 studies are classified as *high*. They follow a global optimization approach for the resource allocation and consider the priority of different available tasks during the resource allocation. Furthermore, they provide a proper evaluation (case study or controlled experiments) and provide at least pseudocode for their implementation. Five studies provide all of this, and additionally, publicly available research prototypes which can be tested and used by researchers and practitioners. Thus, they are classified as *advanced* approaches.

In the following, we want to present the *advanced* approaches in more detail. In the resource allocation approach of Huang et al. [29], the resource allocation problem is modeled as Markov decision processes and solved using reinforcement learning to minimize the process cost. The approach has been implemented in ProM and comparative experiments based on real-world data have been conducted. For minimizing the cycle time, Xie et al. [61] uses a enhanced process model with needed resources and estimated activity execution times as input to a heuristic to assign and also re-assign tasks. The approach is implemented in MathLab and evaluated with comparative simulation experiments and a case study. Arias et al. [2] are using historical process data to identify characteristics on resources, such as their performance, quality, cost, expertise, and workload. This is used as input to the resource allocation problem formulated as integer linear program for identifying the best-fitting resource for a specific case, whereby the priority of different cases is also considered. The approach has been implemented as ProM plugin and also evaluated with comparative simulation experiments and a case study. In contrast to other resource allocation approaches, Ihde et al. [30] allow the specification of resource allocation goals, inputs, and a solution technique on a process activity level. During execution, a resource manager, a new BPMS component, collects the allocation requests for a specific activity and starts the selected solution technique. The approach has been implemented in a research process engine and evaluated in a case study. The focus of Duran et al. [18] is to represent the business process and the resource allocation requirements as Maude simulation model, which can then be used as input to a heuristic for solving the resource allocation. Here, an example heuristic is discussed, but, instead of proposing a concrete one, the method is discussed and approaches from operations research are referenced. The research prototype is publicly available and has been evaluated by simulation experiments.

## 6 DISCUSSION

This survey shows that strong research interest exists globally in the topic of automatic support for resource allocation in business processes, and a broad variety of approaches based on different techniques were developed. In this survey, for the first time, the approaches have been analyzed in terms of their goals, capabilities, input data, used techniques, and their maturity levels. The complexity of the problem to assign tasks to available resources with different capabilities have lead to a variety of approaches with different strengths and weaknesses. Based on the results of the survey, we could observe that some open research challenges still exist, which we discuss in Section 6.1. Furthermore, we discuss the limitations of the survey in Section 6.2.

### 6.1 Main observations and open research topics

*Leveraging process data.* As presented in Section 5.2, most resource allocation approaches identified in this SLR still use a process model with estimations on the process dynamics (e.g., activity duration, arrival rates of new process cases) as input for resource allocation algorithms. However, in recent years, historic process datasets on real-world executions have become more and more available and accessible, such that they can be leveraged for creating a more reliable input for the resource allocation instead of using rough estimates. On the one hand, many approaches already use process data to gain insights about a resource's behavior and preferences. On the other hand, only a few studies use process data to learn the dynamics of the business processes. As a rare example, Djedovic et al. [14] used process data to create a process simulation model.

In this research work, we have provided taxonomies for task and resource attributes, i.e., which input data of tasks and resources were considered for resource allocation. These two taxonomies can be leveraged to identify structurally relevant attributes for the development of new resource allocation approaches. Recent published studies consider additionally resources' preferences [28] and their social context [34, 36, 47, 69] for performing an allocation. These are attributes which seem to be especially relevant for knowledge-intensive processes, where the process is mainly managed by the knowledge of case workers [13].

We could observe that various resource attributes are explored. In contrast, data on task characteristics, such as the priority of tasks, are less used, although they can play a similarly relevant role for finding a suitable resource allocation. Thus, we believe that future research could focus on leveraging process data to learn about the process dynamics, as well as which task and resource attributes are relevant for optimal resource allocations.

*Increase the variability of approaches.* As it can be observed from the results, many approaches focus on human resource allocation and offer approaches with specific allocation goals (e.g., minimizing the process cost). Few offer the possibility to customize the resource allocation goal [18, 29, 30]. Many approaches that were published at business process management outlets follow the idea that the resource allocation approach should be the same for all process activities, whereas in operations research, techniques and heuristics are proposed and developed that match the specifics of a certain activity, e.g., which type of resources are needed. Ihde et al. [30] propose an approach to select a resource allocation technique individually for process activities. Still, the overall process goals and relations between activities should also be considered in such an approach. Furthermore, the selection of techniques is usually driven by trade-off between quality and time to find a solution. In Section. 5.4, we observed that rules for example lead to a fast solution which might not be always optimal whereas linear programming usually provide high quality solution with the disadvantage that it might take very long to get a solution. The primary studies considered in this SLR do not always discuss this aspect in detail. In the future, the trade-off between solution quality and time to find a solution should be more explicitly discussed by the approaches. Additionally, it might be also relevant to develop different versions of the solution approach to support different quality and time goals. In general, interesting future research could focus on approaches that are adaptable to different process settings and show a higher variance in their application possibilities.

*Leveraging machine learning techniques.* With the increase of computational power, processing large amounts of data gets more and more feasible. Therefore, we also noticed a growing trend of approaches which use machine learning techniques to create and/or improve resource allocation algorithms. Additionally, we could observe that the majority of papers using machine learning algorithms improved the quality of the algorithms in comparison to state-of-the-art approaches. From our comparison to other approaches, we can narrow this observation down to the following reason: machine learning approaches tend to create individually adapted algorithms, which often perform better than more general approaches if some assumptions hold. However in the data sets used in the works we looked at, there exists only limited resource information. They only concern the past execution of processes but not information about resources, like the working hours, their capacity, current workload, etc., which are necessary for real world resource allocation. This limitation leads to unrealistic allocations, as this information is not provided. Therefore, we believe machine learning approaches show a promising potential. However, whether they can be applied in real world scenarios has to be shown on more complete data sets.

*Improve evaluation and availability of research prototypes.* When looking at the used evaluation methods and the accessibility of research prototypes in Section 5.5, we can observe that mostly simulation experiments are used and prototypes of research works are often not accessible. Many works have also used comparative experiments to compare their approaches to others. However, the selection of approaches for the comparison was often not done in a structured manner. The results of this SLR can help researchers in identifying other related approaches for an evaluation in a more structured manner in the future. Many prototypes of the discussed studies were not available which hinders the application in practice as well as the comparison between approaches. In future, researchers should place more emphasis on making their approaches, prototypes, and datasets available, ideally following open science principles and leading to replicability and comparability. We could also observe that research prototypes implemented as plugins for platforms seem to have a higher chance to remain available and executable after some years. So far, no benchmarks have been conducted between resource allocation approaches comparing their effectiveness and time, which seems to be a relevant research topic for the future.

### 6.2 Limitations and Threats to Validity

This survey gives an overview on existing approaches for resource allocation in business processes. In an SLR, biases in the selection of the studies and in the data extraction process can be threats to the validity of its results [10]. In the following, we explain steps we took to reduce and mitigate these biases.

For avoiding the selection bias in the study search, we followed a specific search protocol as described in Section 4.2; we further conducted the relevance check based on defined inclusion and exclusion criteria with at least two co-authors, with discussions between them for all cases of disagreements. The primary search needed to be limited by the search terms and was additionally limited by focusing on journal articles. We have observed a broad range of short conference/workshop articles on this research topic, which rather presented idea sketches, such that we decided to focus on more mature work expected to be found in journals. In the secondary search, the backward/forward search, we complemented our search by also considering conference and workshop papers. The study search was initially conducted in mid-2019; in order to consider more recent publications, we have repeated the search in the beginning of 2021. In the full text reading, we excluded duplicates in content and only kept the more mature version of the papers, usually the journal article, to avoid counting one approach more than once. Every exclusion was discussed within a group of co-authors. In sum, we selected 49 primary studies, which we believe to represent of the research field well. Still, the risk exists that relevant studies might have not been included, since they did not meet our search criteria.

Additionally, biases exist in the data extraction process. We also established measures to mitigate this subjectivity. Data coding was done first individually for each paper by different co-authors. Issues and ambiguities were discussed with the co-authors. After having finished the data extraction from all papers, data categories were distributed among the authors and the data extraction per category was validated and standardized. Still, sometimes studies do not provide directly the information on a certain aspect, such that the authors needed to form interpretations.

## 7 CONCLUSION

This survey provided a structured analysis of automatic approaches for the resource allocation in business processes. The structured literature search identified 49 studies providing resource allocation approaches from various countries, published mainly in the last two decades. With this SLR, we studied the following research questions:

- RQ1 What are the targeted resource allocation goals and capabilities?
- RQ2 What is the role of process models and process data (in form of event logs) in the resource allocation approach?
- RQ3 Which input data are used by the different approaches supporting the resource allocation in business processes?
- RQ4 Which solution strategies are used and are the approaches following a local or global optimization?
- RQ5 How mature are the proposed resource allocation approaches in terms of applicability and the availability of an implementation and their evaluation?

Regarding RQ1, we found hat mainly 1-to-1 allocations between tasks and resources are supported, but also studies could be identified which support m-to-1, 1-to-m, and m-to-n allocations. Several optimization goals are followed, such as minimizing process costs, whereby process-oriented goals are mainly supported. We observed with regards to research question RQ2 that often process models and estimations on the process dynamics are used as inputs to the resource allocation approaches, but also process data taken from IT systems play increasingly a role. Furthermore, a taxonomy was developed based on the studies on resource and task attributes, which are used for the resource allocation to answer RQ3. This can be used in future research works to identify possible attributes that can be considered.

Allocation rules have the disadvantage that they do not always lead to the best solution. Nevertheless, they are utilized in many approaches as observed to answer RQ4, because they provide solutions in a short timeframe, which is relevant for many business process. Additionally, the primary studies used heuristics and linear programming as solution techniques, as well as machine learning approaches. The latter ones provide more context-sensitive solutions with the potential of a high solution quality if the training data is of good quality and representative of future cases.

With regards to RQ5, the survey showed that many studies evaluate their approaches with simulation experiments, but only few works provide publicly available prototypical implementations.

On the one hand, the results of this survey can help practitioners to select allocation approaches fitting to their use case. On the other hand, it offers researchers an overview of existing approaches, open research challenges, and a possibility to identify structurally related approaches for comparisons. Although we observed in this study a strong level of research interest in the topic of automatic support for resource allocation in business processes, we also found that several open research topics still exist. The following four main points were deduced: (1) process data could be more leveraged to ensure evidenced-based resource allocation decisions, (2) the variability of approaches could be increased to be applicable in different use cases, (3) machine learning could be more leveraged to provide context-specific solution approaches, and (4) evaluations and availability of research prototypes could be extended to improve the understanding of usefulness and applicability of approaches. In the future, we plan to establish a benchmarking platform for resource allocation approaches for allowing better comparisons on the functionality and complexity of the approaches.

## 8 ACKNOWLEDGMENTS

The research leading to the results presented here has been partly funded by the BMWi under grant agreement 01MD18012C, Project SMile. http://smile-project.de

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