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Faculty of Business Economics

Master of Management

Master's thesis

The resource perspective in process mining: a systematic literature review

Emma Van Coillie

Thesis presented in fulfillment of the requirements for the degree of Master of Management, specialization Business Process Management

SUPERVISOR :

Prof. dr. Niels MARTIN

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Process mining analyses data from information systems to find, track, and enhance processes as they actually are. A process is a series of steps undertaken to achieve a goal. Those steps are undertaken by an employee, a.k.a. a resource. One of the many perspectives that can be adopted while mining processes is *"the resource perspective"*. Using pre-set criteria, a systematic literature study was conducted on the resource perspective in process mining. The literature was looked at from four foci: general descriptives, process mining lens, resource perspective lens, and industry lens. Each foci contains a number of topics, of which in total there are ten. The discussion of this thesis focuses on general trends, domain expert evaluation, sector potential, Industry 4.0, and advanced analysis of included topics, which each created their own opportunities for future research. This thesis is the first contribution to the study of the literature on the resource perspective in process mining.

Keywords *– Process mining; resource perspective; organisational perspective, literature review*

Acknowledgements: I'd like to say thanks to Prof. Dr. Niels Martin for his invaluable patience, feedback and help as my supervisor. This endeavour would not have been possible without Dr. Iris Beerepoot from Utrecht University, who was part of realising the methodology for this article. I also wish to acknowledge the help provided by Thomas De Lombaert for helping me finalise the text.

1. Introduction

The basis of process mining is the practice of analysing company processes utilising execution data of corporate information systems (van der Aalst, 2016). Information systems, including workflow management systems (WFMSs), enterprise resource planning (ERP), and customer-relationship management (CRM) systems, have been used to generate input to make models (Aghabaghery et al., 2020). Traditional model-based process analysis (e.g., process simulation) and data-centric analysis approaches such as machine learning and data mining are linked by process mining (Agostinelli et al., 2020).

Currently, with the capabilities of computer technology, any business is able to record all operational occurrences in its system. The firm can do additional analyses using recorded occurrences (Utama et al., 2020). As stated by Guzzo et al. (2021), event logs are a set of process executions in a real-life application. Stated differently, it is a set of events that happened in reality, rather than how they were supposed to happen in theory. The event logs contain information like performed activities, resources, and timestamps. This data can be used for analysis along with several behaviour perspectives. An example of a commonly used perspective is the control-flow perspective, which focuses on the tasks that are done and their sequence.

The resource perspective is another of process mining's numerous views. Human resources are of the highest significance since they ensure the proper execution of business operations (Cabanillas, 2016). Also known as the organisational perspective, the resource perspective is concerned with the resource entity, that is, which resources are involved, how they are connected, and how they operate (Yahya, 2014).

In recent years, research interest in process mining has increased, as seen by the numerous literature reviews on the topic. For example, Garcia et al. (2019) have mapped process mining techniques and applications. Moreover, several authors (e.g. Rojas et al., 2016; Ghasemi and Amyot, 2016; De Roock and Martin, 2022) have focused on systematically analysing literature about process mining in healthcare. Yet no equivalent effort has been put in for the often disregarded resource perspective in process mining, because it has been accorded a lesser importance than other perspectives (Huang et al., 2012). Process mining solutions for perspectives such as the organisational perspective are limited (Schonig et al., 2016). Additionally, while much academic effort has been devoted to the control flow component of business processes, organisational aspects of processes have frequently been disregarded (Ly et al., 2006). Yet resources ensure that operations can proceed, they play a critical role in many corporate processes (Martin et al., 2020). Hence, the focus of this thesis is on exploring the resource perspective in process mining through a systematic literature review.

The primary research question of this thesis is: "*What areas have been primarily addressed in publications on the resource perspective in process mining?*". This question will be answered through four foci: general descriptives of the data, process mining lens, resource perspective lens, and industry lens. The purpose of this thesis is to present results of a systematic literature review on the resource perspective in process mining, which has not been done before. This paper provides the most recent overview of relevant literature, and categorises the literature according to relevant topics. It explores the evolution of the research domain, and provides gaps in the literature that are indicated for future research to fill.

The remainder of this paper is structured as follows. Section 2 consists of preliminaries explaining important topics for background information. The methodology is described in Section 3. Section 4 presents the findings of the systematic review of the academic literature. Section 5 consists of a discussion of the results. Following that, a conclusion is given on the critical information from the findings in Section 6.

2. Preliminaries

Process mining

Process mining is a field of study that allows decision makers to extract process models from event data, compare expected and actual process behaviours, and enrich/repair process models using data (Agostinelli et al., 2020). The field lies between computational intelligence and data mining on the one hand, and process modelling and analysis on the other (van der Aalst et al., 2012). Process models can be thought of as "maps" that describe the operational processes of an organisation (van der Aalst, 2014).

The difference between process design and process mining is as follows. Traditional process design begins with the creation of a process models (e.g. BPMN), while process mining begins with the collection of data about processes as they actually occur (van der Aalst and Weijters, 2004). During the processing of a case or instance of a process, databases are used to store information about how activities are carried out, these data are utilised to obtain insight into the actual execution of operations (Mannhardt, 2018). These data are used to build an event log.

An event log is used as the starting point for process mining. A basic definition of an event log would describe it as a collection of process operations that record the various business activities (Sarno et al., 2015). A sample of an event log can be seen in Table 1. For example, we can see that Stef uploads on May 5th, which is a part of Case ID 56.

An event or activity refers to a specific action (i.e., a well-defined phase in the process) that is associated with a specific case (Ebrahim and Golpayegani, 2021). A case is a list of events that happened during a single run of a process, it can be thought of as the way something is made (Sarno et al., 2015). From this information, process models and other information can be extracted with algorithms.

Table 1. Illustration of event log structure.

Case ID	Timestamp	Activity	Resource
...	…	…	…
55	2022-05-03 16:55:06	Upload	Stef
55	2022-05-03 17:58:43	Admit	Nienke
56	2022-05-05 18:03:33	Register	Hendrik
56	2022-05-05 10:06:54	Verify	Stef
56	2022-05-05 10:30:50	Upload	Stef
56	2022-05-05 10:46:29	Admit	Nienke
57	2022-05-07 11:16:12	Register	Hendrik
57	2022-05-07 11:44:32	Verify	Stef
…	…	…	…

Perspectives

There are several perspectives in which process mining can be looked at. The control-flow perspective is the most common viewpoint. The control-flow perspective focuses on the order in which activities are done. It is a common misperception that process mining is confined to control-flow discovery (Dakic et al., 2018). Other perspectives, such as the data perspective (modelling decisions, data creation, forms, etc.), the time perspective (modelling durations, deadlines, etc.), and the function perspective (describing activities and related applications), are frequently mentioned but receive less attention (van der Aalst et al., 2016). The perspectives are explained in detail under Section 4.2. The resource perspective is discussed in greater detail in the next paragraph, as it is the thesis' scope.

The resource perspective, also known as the organisational perspective, is the perspective of the employees (and sometimes machines) from a modelling standpoint. The objective of process mining from an organisational viewpoint is to discover responsibilities and roles, work allocation among performers (resources), and tasks that a given resource may execute (Gupta et al., 2014). When looking at the log from an organisational viewpoint, it is important to consider the information about the players or performers (e.g., people, systems, roles, or departments), how they are engaged, and how they are linked. Mining the organisational perspective should provide a response to the question "*Who*" is executing the process activities and how they are connected, e.g., the frequency in which a case is passed from one performer to another in the process (van der Aalst et al., 2012).

3. Methodology

This thesis used a qualitative technique, namely, a systematic review of the literature. The goal of a systematic literature review is to find, evaluate, and put together all the empirical evidence that meets the criteria set out ahead of time to answer a certain research question (Higgins et al., 2019). The purpose of this paper was to evaluate and assess the available literature on process mining from the standpoint of the resource perspective. There were a number of steps involved in compiling the relevant literature sample. The methodology for the literature review was developed by prof. Dr. Niels Martin (Hasselt University) and Dr. Iris Beerepoot (Utrecht University) as part of a larger research project. Moreover, they completed stages 0 (preparation) through 3, and provided the selection of papers after stage 3 to the author of this paper. The path from 1246 articles to 163 articles is depicted in Figure 1 using a PRISMA flowchart.

Preparation (given in Martin and Beerepoot (2022))

As given by Martin and Beerepoot (2022), the initial stage, or ‘0’ stage was meant to finetune search terms, dimensions, and inclusion-and exclusion criteria. This stage was done by exploring literature on databases such as Web of Science, IEEE Xplore, ScienceDirect, Google Scholar. Research criteria are built upon following search terms: ("process mining" OR "workflow mining" OR "event log" AND "resource" OR "originator" OR "staff" OR "actor" OR "employee" OR "organisational" OR "organisational") that could occur in title, abstract or keywords.

- Inclusion criteria:
  - IN1: The paper has explicit attention for the resource perspective in process mining within an organisational context.
- Exclusion criteria:
  - EX1: The full-text of the paper is not available;
  - EX2: The paper is not written in English;
  - EX3: The paper has not been published in a peer-reviewed scientific journal or in peer-reviewed conference proceedings;
  - EX4: The paper is a one-pager, executive summary, abstract, editorial, research proposal, interview, poster, call for papers or table of contents;
  - EX5: The paper focuses on process mining in an organisational context, but a resource-related topic is insufficiently part of the core of the paper;
  - EX6: The paper focuses on a resource-related topic, but process mining in an organisational context is insufficiently part of the core of the paper;
  - EX7: The paper neither focuses on a resource-related topic, nor on process mining in an organisational context in the core of the paper.

Stage 1 (given in Martin and Beerepoot (2022))

As stated by Martin and Beerepoot (2022), the first collection of publications were identified in Stage 1. Primary databases Web of Science and IEEE Xplore, as well as secondary databases ScienceDirect and Google Scholar, were used to conduct literature searches. At this point, duplicates were also deleted. The query was executed on September 27 2021. There are no publications included in the coding of the literature that were published after this date.

Stage 2 and stage 3 (given in Martin and Beerepoot (2022))

In accordance with Martin and Beerepoot (2022), the papers were screened for the first time in stage 2. The title was read, and the inclusion and exclusion criteria were used. This was conducted independently by both Dr. Niels Martin and Dr. Iris Beerepoot. There was an instant consensus on 670 publications. This indicates that either both coders selected "include" or "exclude" based on the same exclusion criterion.

In stage 3, a preliminary dispute existed for 252 items when both coders indicated “Exclude”, but employed a different exclusion criterion, resulting in an initial disagreement. Items on which there was dispute were discussed in order to find a consensus. The papers were screened for a second time in order to make a final selection. The same method was used as in stage 2. This review covers academic and conference papers ranging in publication date from 2004 to 2021. In total, around 199 sources were included for this selection. The following are the final decisions on the 922 items that served as the starting point for this stage:

- Include: 199 items;
- Excluded – EX1: 0 items;
- Excluded – EX2: 0 items;
- Excluded – EX3: 41 items;
- Excluded – EX4: 39 items;
- Excluded – EX5: 475 items;
- Excluded – EX6: 27 items;
- Excluded – EX7: 141 items.

Stage 4

This is the stage where the author of this thesis was brought in. The goal of stage 4 was to extract relevant information from the selected papers. The papers were read, and relevant information was put in an Excel spreadsheet provided by Martin and Beerepoot (2022), which contained the coding scheme. The total amount of papers read through was 199. At this point, articles could still have been eliminated, and finally 163 articles were utilized for analysis. 36 papers (18,1%) were eliminated in total, respectively due to EX5 (31 papers), EX6 (2 papers), EX2 (2 papers) and EX1 (1 paper). The author read each publication's abstract, introduction, conclusion, and methodology in that sequence. If further information was required, the results and discussion sections were also reviewed. In Section 4, the sought-after information from each study will be discussed in depth. A complete list of used literature can be found in Appendix 8.1.

Stage 5

The final stage was synthesising the obtained data and drawing conclusions. To derive conclusions from the data, Microsoft Excel pivot tables and graphs were used.

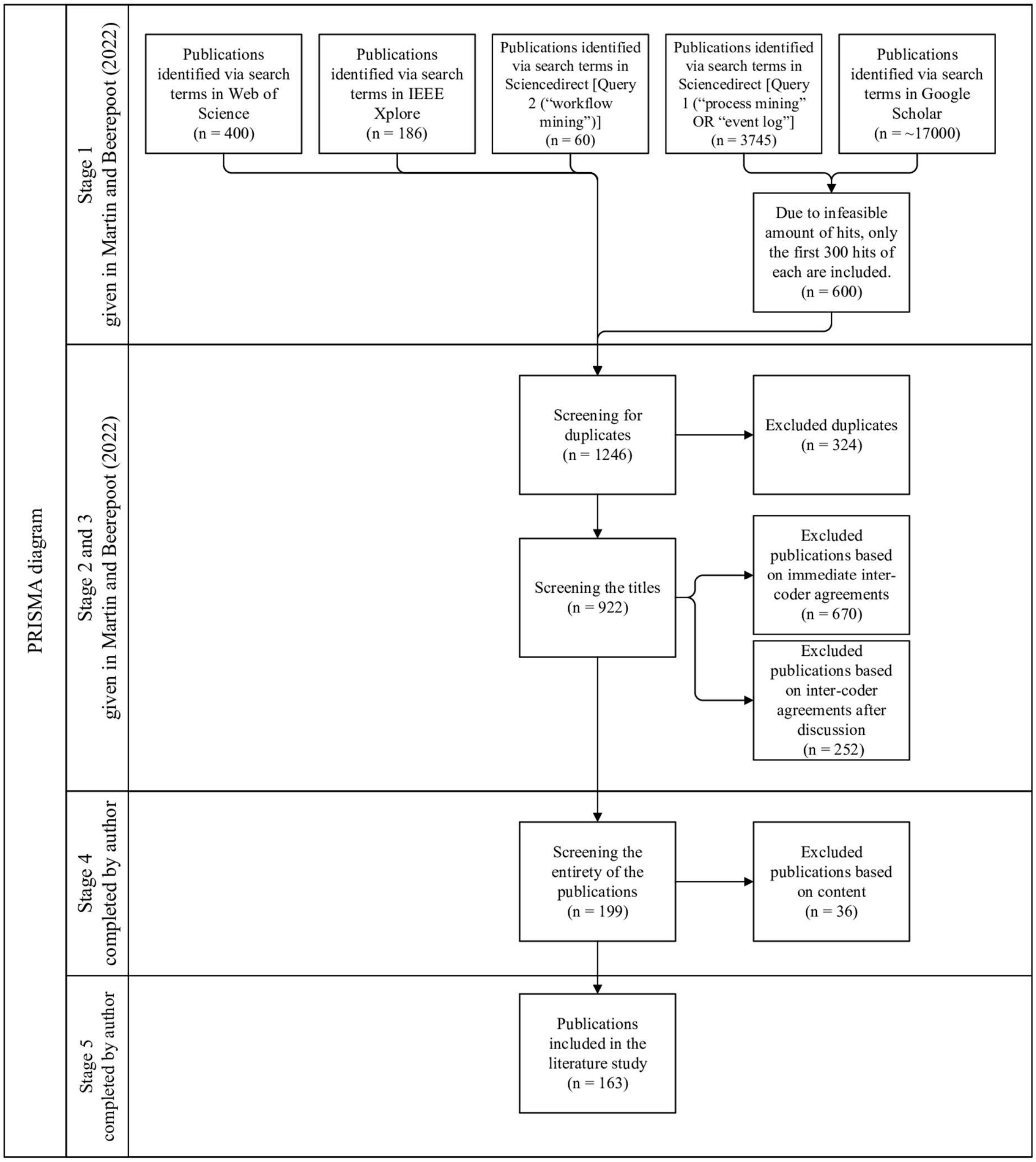

Figure 1. Search strategy in a PRISMA diagram.

4. Results

This section discusses the findings of the literature review about the resource perspective in process mining. It also categorises the final selection of 163 papers based on a variety of review dimensions. For example, this section examines the regularity with which different views and types of process mining arise, which scopes are used for the resource perspective, and the industries in which they have been implemented. Following that, the findings are summarized, and the most significant observations are addressed in detail.

Four foci are discussed in this section, and in total 10 topics (see Table 2). The purpose of these different foci is to give a general overview of the current state of the resource perspective in process mining. The first focus is general descriptives, which place the read material in context. It includes nature of publications, and paper focus. The second focus is the process mining lens, which covers analysis type, process mining type, and process mining perspectives. The third focus is the resource perspective lens, which is comprises the resource scope, organisational scope, and use case. The fourth focus is the industry lens, and looks at the purpose sector, and evaluation with domain experts. Each topic is explained in general with a sample description and following that, examples are given of relevant articles to demonstrate and clarify the notions.

Table 2. Structure of Section 4.

Foci	Topics
4.1 General descriptives	Nature of publications, paper focus
4.2 Process mining lens	Analysis type, process mining type, process mining perspectives
4.3 Resource perspective lens	Resource scope, organisational scope, use case
4.4 Industry lens	Purpose, evaluation with domain experts

4.1. General descriptives

The general descriptives' primary function is to offer a description of the articles that have been included in the study.

Nature of publications

A time span of 2004 to 2021 is covered by the publications. There were 74 (45,40%) journal articles and 89 (54,60%) conference papers among the 163 items. In 2021 there were no conference papers, and this was due to several possible reasons. An example can be that it is a consequence of COVID-19 and the lack of conferences because of it. Another possible explanation lies in the fact that the query was executed on September 27 2021, and thus part of the conferences may not have been included. A general rise in interest is seen in the topic, but that can be ascribed to several possible reasons. For example, process mining as a field has grown in general. Due to a positive trend (see Figure 2), which suggests that the topic will presumably be researched even more in the coming years.

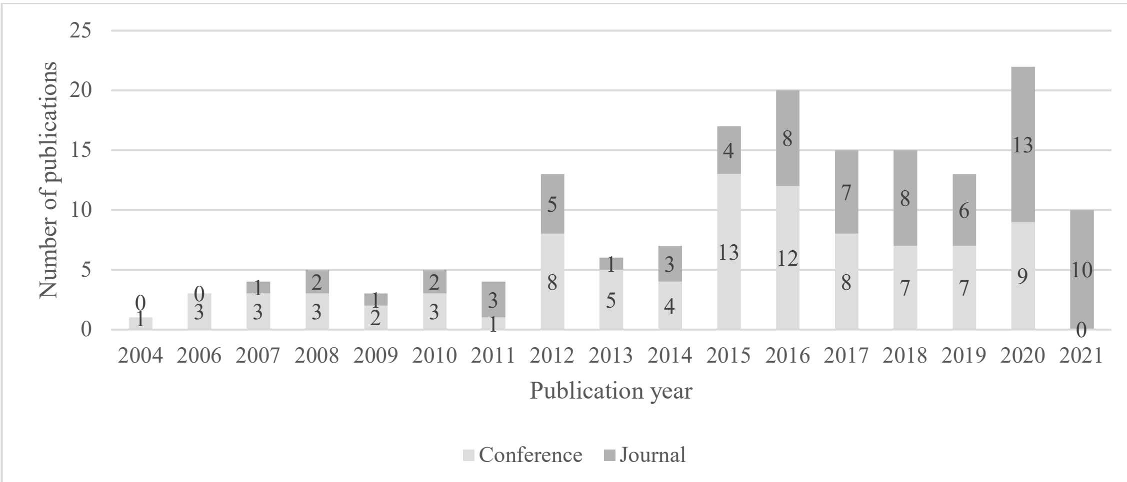

Figure 2. Overview of published articles and conference papers on the topic of the resource perspective in process mining over time.

Paper focus

The focus of the paper reflects the type of research that was carried out for the publication. There are four paper focus types (see Table 3), namely conceptual contribution, method development, method application, and method development and application. Each paper focus type is explained in the next paragraphs with example papers.

The first type is a *conceptual contribution*, which appeared 17 times (10,43%). This type of focus means that the paper contributes solely conceptually. This indicates that the work neither proposes nor applies a new method (executable or directly implementable). An example of a conceptual contribution is the paper of Tang and Matzner (2020), as they wrote about process mining from a sociotechnical perspective via a work systems theory, as thus no new method was proposed nor applied. Work systems theory ties together people, information, and technologies so that work (processes and activities) can be done within a work system. The theory shows how important it is to match processes and activities with people, information, and technologies. It makes it clear that each of these things is a separate but connected part of the work system. The sociotechnical perspective conceptualises the social and technical as interdependent and comparably important components within a system (Alter, 2013). The same goes for the paper of Arias et al. (2018b), where the authors conducted a literature analysis to determine the criteria utilized in resource allocation strategies.

The second type is *method application*, which appeared 19 times (11,66%). This type does not suggest a new technique, but rather applies an existing (or multiple) unique real-world scenario(s). An example of this type is the paper of Ni et al. (2011). In this paper, two methods, organisation mining based on performer similarity (1) and organisation mining based on grid clustering (2), are shown to work. Organisation mining is process mining from the resource perspective. Performer similarity means the parallel of tasks between resources. The grid clustering method is a technique for managing larger event logs for calculations, but has the same goal as the organisational mining based on performer similarity. The methods can get the real organisational structure of a business from the enterprise information system's event log, especially regarding similarity of tasks.

The third area of focus is *method development*, in which the article suggests a novel approach but does not apply it to a real-world setting. It emerged 29 times (17,79%). The procedure might have used toy data (for demonstrative purposes) or artificial data in a more systematic fashion. An example of method development is the paper of Raitubu et al. (2019), they applied an agile approach for software development performance analysis assessment. Another example is the paper of Hanachi et al. (2012) where the authors want to improve event logs by adding a performative-based resource communication language. Simply put, this means that exchanges between resources can be incorporated in the event logs. On the basis of those enhanced logs, the authors subsequently demonstrate innovative mining methods for identifying organisational processes. Both papers used toy data to demonstrate their work.

The fourth type is *method development and application*, in which the article suggests a novel method and implements it in one or more specific real-world context(s). This type appeared 98 times (60,12%). An example article is that of Pan and Zhang (2021), in which a new process mining framework for building information modeling-based project management is introduced. The goal of this framework is to capture and explore the nature of the complicated process and cooperation that occurs during the building process. To verify the approach, a case study is conducted on a three-story building construction project in the Netherlands. A second example of method development and application is the paper of Stefanini et al. (2020). The authors developed a process mining-based strategy to systematically enhance resource planning in healthcare. In other words, they attempted to create a method through the use of process mining that would allow them to make a planning for the employees. The method was applied to a case study of lung cancer patients at an Italian hospital. The authors found that the method was successful and easily scalable.

Table 3. Overview of paper focus.

Paper focus	Publications (in #)	Publications (in %)
Conceptual contribution	17	10,43%
Method application	19	11,66%
Method development	29	17,79%
Method development and application	98	60,12%
Total	*163*	*100%*

4.2. Process mining lens

The topics in this subsection all pertain to process mining. Specifically, this indicates that the articles are appraised based on common process mining subjects.

Analysis type

There can be made a distinction in type of analysis in the process mining field. There are three types of process mining: predictive, prescriptive, and descriptive (see Table 4). These three types aim to answer the questions '*What is going to happen*?', '*What is the best action we can take*?', and '*What is going on*?', respectively (Hertog, 2016).

Predictive analysis was mentioned the least, more specifically it was only found 10 times (6,13%) in 163 papers. A predictive process analysis example can be found in Sun et al. (2020). The authors create a model to look at how multiple processes running at the same time compete for the same resources, and in consequence predict the time it takes for those processes to run.

Prescriptive analysis was detected almost as much as predictive analysis, namely 11 times (6,75%). The publication of Arias et al. (2016b) shows a prescriptive type of analysis. They offer a process mining-based framework for recommending resource allocation at the sub-process level, as opposed to the activity level, thus they prescribe the right resources to tasks based on sub-process levels.

The most common type of analysis is *descriptive analysis* with 142 papers (87,12%). An example of *descriptive analysis* is the article of Senderovich et al. (2016a). The main goal of this publication is to find resource queues. In particular, they aim to describe how the information in an event log affects queue lengths, or the number of cases waiting for an activity.

Table 4. Overview of type of analysis.

Type of analysis	**Publications (in #)**	**Publications (in %)**
Predictive	10	6,13%
Prescriptive	11	6,75%
Descriptive	142	87,12%
Grand Total	*163*	*100%*

Process mining type

As explained in van der Aalst et al. (2012), process mining is classified into three types: discovery, conformance, and enhancement. The sample description is expressed in two ways. The first way is about how many publications contain a specific topic type (number of publications), which means that the number of appearances are set against the number of read publications, which is 163. This overview can be found in Table 5. The second way is about how many times a specific topic type appears across publications (number of appearances) to find the proportions. This is because an article can have multiple of these topics ascribes. The sum of these topic type appearances will not be 163, and are in Figure 3 to present a clearer outline of how they are shared among articles.

Conformance appeared in 21 publications (12,8%). *Conformance* compares an existing process model to an associated event log in order to determine whether reality, as captured in the log, conforms to the model and vice versa. Mannhardt et al. (2016) evaluated the conformance of an existing model by experimenting with several methodologies on event logs.

Enhancement emerged 26 times in publications (15,95%). It is the process of expanding or improving an existing process model by utilizing information about the actual process as recorded in the event log. A model that does not suit the process can be corrected utilizing the diagnostics offered by the model-log alignment. Burattin et al. (2013) used role discovery process mining to enhance existing models with information about resource roles.

Discovery is the most used process mining approach, being found in 152 publications (93,25%). It produces a process model from an event log without requiring prior understanding of the process. Process discovery generates models automatically from observable events. De Weerdt et al. (2015) authored an article solely devoted to discovery. Their work proposes a BPMN Miner, a process discovery approach that uses BPMN as the language used to express the result of the discovery.

Table 5. Overview of process mining type.

Process mining type	**Appearance in publication (in #)**	**Appearance in publications (in % of 163)**
Conformance	21	12,88%
Enhancement	26	15,95%
Discovery	152	93,25%

Figure 3 depicts a Venn diagram that is used to determine the proportions of overlapping appearances. We see that the proportion of discovery relative to the other categories was 77,78 %. 4,94 % in conjunction with conformity and the same amount in conjunction with improvement. Conformity appeared 1,23 % without enhancement and 0,62 % with enhancement. Enhancement appeared by itself at 4,32 % of the time. All three categories combined accounted for 6,17 % of the publications.

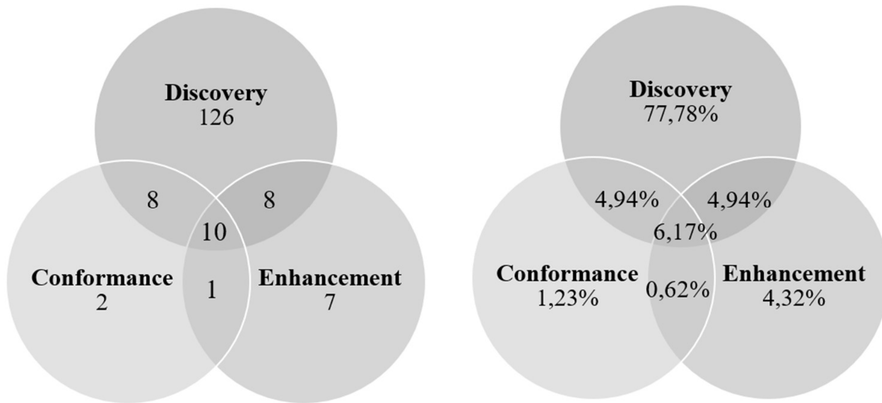

Figure 3. Venn diagrams of process mining types (left in #, right in % to compare among perspectives).

Process mining perspectives

There are other perspectives in the process mining world than the resource perspective. The perspectives included in this article, next to the resource perspective as the main focus, are time perspective, function perspective, control-flow perspective and data perspective, as shown in Table 6. The total number of publications does not equal 163, since publications could have more than one perspective ascribed. It shows how many publications contain a specific topic type (number of publications), which means that the number of appearances are set against the number of read publications, which is 163. For clarity, a complete table of the publications per perspective is given in Appendix 8.2.

The *data perspective* was the least common with 82 publications (50,30%) that contained this perspective. The *data perspective* specifies which existing data items are required as input throughout the process's execution and are utilized to make control-flow routing decisions (Mannhardt, 2018). The paper of Havur and Cabanillas (2019) is an example of the data perspective. In their paper, they describe a new approach that breaks up a process in a way that takes risk into account to allocate resources. Given historical execution data and a process fragmentation threshold, the method improves the feasibility of resource allocations by dynamically generating the process pieces that meet the probabilistic threshold in a way to take risk into account. Process fragmentation is the distribution of process across the organisation, since it is typical for processes to be cross-departmental or even cross-organisational. This makes it impossible for a single body to have complete control or even visibility over the whole process flow (Hens et al., 2014).

The *time perspective* concerns the timing and frequency of occurrences, and appeared 94 times (57,67%) in publications. With timestamps attached to events, it is feasible to identify bottlenecks, quantify service levels, monitor resource use, and forecast the remaining processing time for ongoing instances (van der Aalst et al., 2012). An example paper that uses the time perspective is Sun et al., (2020). The authors provide a technique for estimating the duration of business operations. They have a set of features that take into account how instances compete for resources. They also choose and rank a few key activities that have a big effect on the execution time.

The *function perspective* is concerned with the processes themselves, and it appeared 104 times (63,80%) across the publications. The function perspective is about describing activities and related applications (van der Aalst et al., 2016). An example of the *function perspective* can be found in Low et al. (2017), where methods are developed to visualise data that will aid in the targeted examination of resource reallocation and activity rescheduling. With the proposed visualisations, analysts are able to identify changes in resources and time that led to a reduction in overall costs.

The *control-flow perspective* focuses on the order in which activities are done, and it emerged 112 times (68,71%). Control-flow mining creates process models automatically from process logs, the developed process model corresponds to the actual process as observed during actual process executions (Mans et al., 2008b). Bozkaya et al. (2009) have authored a work that exemplifies the control-flow approach well. They present a process diagnostics technique that provides a comprehensive overview of the information system-supported process. The outcome of their research reveals the actual process model. The output of the approach can be utilised to do more research on particular topics.

Table 6. Overview of perspectives.

Perspective	Appearances (in #)	Appearances (in % of 163)
Data perspective	82	50,30%
Time perspective	94	57,67%
Function perspective	104	63,80%
Control-flow perspective	112	68,71%

4.3. Resource perspective lens

All of the subjects under this subsection belong specifically to the resource viewpoint in process mining. In particular, this signifies that the articles are evaluated using typical indicators of the resource perspective. Each resource perspective topic has its own comprehensive table that provides an overview of the relevant literature in Appendix (Section 8).

Resource scope

The resource's scope can be one of the four following cases: individuals, dyads, teams, or there was no resource scope assigned. An overview can be found in Table 7. During the coding process, no articles focusing on dyads were discovered, that is why this element is also not in the table. A table offering an overview of the complete literature list per resource scope type can be found in Appendix 8.3.

The *not assigned* case is included because the resource scope is unclear or does not fit in the other categories, and occurred in 5 publications (3,07%). An example of this resource scope is the paper of Matzner and Scholta (2014). Their research is a literature review on organisational mining, and identifies 18 different approaches to detect organisational properties in cyber-physical systems. This study was conducted without a specific resource scope in mind, as the approaches do not specifically target a resource scope. A cyber-physical system's application fields include sophisticated automotive systems, traffic management, smart grids, process control, medical systems, and manufacturing, among others (Shi et al., 2011).

The *team* scope is when the paper aims to find information on resources on the level of a group of employees, and it emerged 75 times (46,01%). An example is the paper of Sellami et al. (2012), they discover relationships between performers in a workflow. Relationships, in this case, are the organisational structure and the communication between performers in the process. A second example is the paper of Lai and Liu (2008). Specifically, they discuss an algorithm for mining the group-based knowledge flow from workers who have similar knowledge flows. A knowledge flow circulates and accumulates information inside an organisation to support resources' activities.

The last resource scope that is included is the *individual resource*, which appeared 83 times (50,92%). The article of Y.B. Liu et al. (2007) is about individual resources in terms of the resource scope, specifically a machine learning technique that suggests an appropriate actor to carry out specified actions. Nakatumba and van der Aalst (2010) wrote about an approach to quantify the relationship between workload and processing speed. They correlate the processing speed of a resource with its workload.

Table 7. Overview of resource scope.

Resource scope	Publications (in #)	Publications (in %)
Not assigned	5	3,07%
Team	75	46,01%
Individual resource	83	50,92%
Total	*163*	*100%*

Organisational scope

The publications can focus on settings where just one department of a company is involved, or multiple departments within a company, or even a setting where multiple organisations are combined (see Table 8). The *not assigned* case is included for when the organisational scope is ambiguous or does not match the other categories, and assigned to 8 publications (4,91%). Appendix 8.4 provides an overview of the comprehensive literature list by organisational scope type.

The setting of *several organisations* was used only 3 times (1,84%). An example that had several organisations as a setting is the publication of C. Liu et al. (2020). Their focus was emergency response process mining. Cross-organisation emergency response processes (CERPs) are a group of processes that work together to deal with emergencies that involve more than one organisation. Building a CERP takes a lot of time and is prone to mistakes. People who develop it need to have a lot of experience and business background. The publication of C. Liu et al. (2020) focuses on solving this problem by creating CERPs with process mining.

A *not assigned* setting can be found in the paper of Sikal et al. (2019). The main point of their work is to suggest a pattern that gives a detailed view of resource variability discovery in configurable processes. Taking into account the activity's variability specification file, an algorithm is proposed to find the variation points and their different versions. Also, the pattern makes it possible to find variability in data. Modeling business process variability captures variability in all process parts through a flexible method. A customizable process has activities, resources, data, and events. Business process variability relies on variation points and variants. Variation point is where variability occurs, and variant is its realisation. There is no assigned organisational scope in this paper.

The *several departments of a single organisation* setting targets processes that function across departments in the same company. It appeared 16 times (9,82%). The publication of Wang et al. (2016) is an example of this. This article presents a novel method for analysing how departments collaborate in the joint logistics chain. Techniques for process mining are used to identify patterns on how work is performed within the organisation.

A *single department of a single organisation* is by far the most common scope with 136 appearances (83,44%). The paper of Sakchaikun et al. (2018) is an example of such a setting. The authors use data that were collected from a single department in a single company, more specifically from an IT service department. They employ process mining to assist the organisation improve the quality of its customer service, resulting in better customer happiness and enhanced efficiency.

Table 8. Overview of organisational scope.

Organisational scope	Publications (in #)	Publications (in %)
Several organisations	3	1,84%
Not assigned	8	4,91%
Several departments of single organisation	16	9,82%
Single department of single organisation	136	83,44%
Total	*163*	*100%*

Use case

The use case illustrates how process mining may be beneficial from a human resource point of view. Seven use case types are identified across all the publications. The total of the use cases does not equal 163 since publications could have more than one use case type ascribed. In Figure 4 there is a pie chart with the absolute number of appearances in publications, and percentages of appearance in proportion to each other. Each use case is explained and substantiated by examples in the following paragraphs. A complete table with each publications sorted per use case can be found in Appendix 8.5.

Resource assignment is the first and most common use case, which appears 51 times (24%). Resource assignment focuses on how to allocate resources efficiently to optimize process performance (Zhao et al., 2015). This use case includes task analysis, team makeup, and resource recommendation. Y.B. Liu et al. (2008) developed a method for semi-automatic staff assignment in workflow management systems. A second example of resource assignment would be the publication of Lee et al. (2019). If the initial human resources become unavailable, the authors suggest using a methodical approach that involves analysing event logs to choose suitable substitutes. The selection of suitable substitutes is based on the degree to which the work experiences of the initial human resource and substitute resource are similar to one another.

The second use case is *resource behaviour and performance quantification*, which appears 47 times (22%). This use case examines examples of resource actions, performance, and abilities. In addition, analysis of similar resources and value creation are included. An example of this use case is Huang et al.'s (2012) article. They introduce an approach for assessing resource behaviour using process mining from four crucial vantage points, namely, resource preference, availability, competence, and collaboration.

The third use case, *social network identification*, appears 42 times (19%). This use case derives roles and other organisational entities from the event log, so the focus is on the relation between people or groups of people and the process, or on the relationships between people (Reungrungsee et al., 2012). An example of an article that uses *social network identification* is Jafari et al. (2020), where they illustrate how individuals participate in and influence the communication network. They also underline the importance of effective communication in enhancing process efficiency. The results quantify the communication network and emphasize the involvement of key resources.

The fourth use case is *control-flow discovery*, which is a sort of analysis that focuses on discovering the order of business process operations. This use case emerges 31 times (14%). By studying the order in which tasks appear in the event log, it should be feasible to develop a model that explains the process's overall behaviour (Ferreira, 2020). An exemplary article is the publication of Rozinat et al. (2009). This research demonstrates that simulation models can be automatically constructed from event logs. These simulation models must encompass multiple perspectives, including control flow, data, resources, and time, among others. Consequently, they demonstrated that each of these views can be unearthed using conventional process mining approaches, and that all mining results may be combined into a single simulation model.

The next use case is *conformance and anomaly analysis*, which occurs 18 times (8%). This sort of use case examines exceptions and existing process models for differences. An example is Allen and Tilbury (2012), they present a novel anomaly detection technique for event-based systems composed of processes that interact through shared resources and that lack a formal model. This method builds models, evaluates the performance of the models in fault detection, and then employs the models and their performance to find abnormalities in fresh event streams.

Work organisation mining is the sixth use case type, it appears 14 times (7%). This type is about the organisation of work and analysis of work conditions. Ogunbiyi et al. (2021) is an example paper on this use case type. The paper states that until now, the humanistic impacts of process mining, such as job satisfaction and workload, have been mostly ignored. This ongoing report explores process mining from a sociotechnical point of view. They use work systems theory to think about how process mining can be used to improve work conditions by getting processes and employees in a work system to work in a more harmonic way. Work systems theory emphasises the necessity to match processes and activities with relevant people, information, and technology (Tang and Matzner, 2020).

The last use case type is *resource role identification*, and it emerges 12 times (6%). This type attempts to identify resource roles. An example is Jin et al. (2007). The authors developed a technique for role mining that utilises event logs as the primary kind of input, where they specifically look at shared activities to define roles. However, there are too many resources that aren't linked to each other to identify roles. There are always some people who are focused on tasks that no one else has done yet, making it hard to link them to specific roles. Another example is the paper of Porouhan and Premchaiswadi (2015). They used a method called role hierarchy mining in order to examine the roles that each participant played during the training programme of an academic writing course.

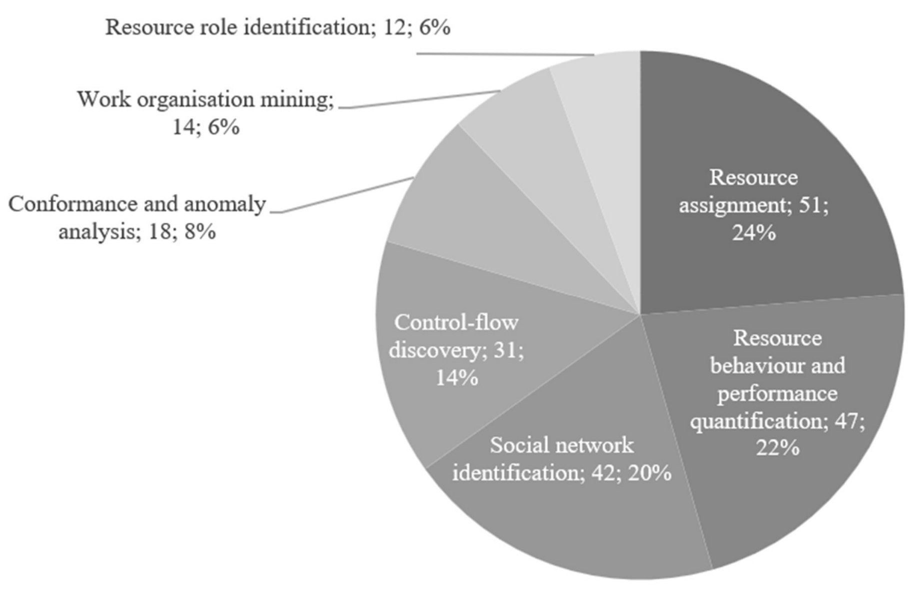

Figure 4. Use case types by number of appearances in absolute numbers and percentages.

4.4. Industry lens

The objective of this focus is to investigate the present state of the resource viewpoint in process mining in relation to the industry as it exists in the actual world. This subsection focuses on the industries to which articles were tailored and whether input was received from domain experts.

Purpose

The purpose focuses mostly on whether or not the approach is sector-specific. An overview is provided in Table 9. There were 128 (78,53%) publications with a general purpose, and 35 (21,47%) for a specific sector. To identify the specific sectors for which one out of five the articles were written, the Statistical Classification of Economic Activities in the European Community, Rev. 2 (2008) were used during coding. See Appendix 8.6 for an overview of this classification.

A *general purpose* article explains or implements a method that can be applied regardless of the sector or process. An example paper of a publication with a general purpose is Jin et al. (2007). Without a specific industry in mind, the authors offer a method of role mining that uses event logs as input. This strategy is applicable regardless of sector.

Table 9. Overview of purpose of publications.

Purpose	Publications (in #)	Publications (in %)
General purpose	128	78,53%
Specific for sector	35	21,47%
Total	*163*	*100%*

As seen in Table 10, *education* appeared 2 times (5,71%). An example is the publication of Rasyidi (2017) where the university employees attendance log is analysed in order to acquire insights in the improvement of policy as well as to understand the behaviour of employees before the development of an attendance information system. Staffs are more punctual than faculty, according to the paper. Although the average daily labour length of faculty is larger than the university mandates, some may work less, which needs examination. Various flaws were found with university policy that need to be rectified.

Manufacturing appeared 3 times (8,57%). An example where *manufacturing* was the center of attention is the publication of Yahya (2014). The author addressed the issue, "*How can the notion of process mining be implemented in a manufacturing environment?*". In response, the paper demonstrates the application of industrial process analysis using process mining. The paper leverages existing process mining techniques and suggests an event data visualisation utilising annotation charts.

Next is *information and communication*, which also emerged 3 times (8,57%). Specifically the publication of Gupta et al. (2014) is an example of where this purpose sector appeared. The authors conduct a case study using data from the Google Chromium project to demonstrate the efficacy of the proposed methodology and applications. In addition to control flow analysis, they mine event logs to do organisational analysis and uncover metrics such as work transfer, subcontracting, joint cases, and joint activities.

Human health and social work activities is the most researched subject in the resource perspective in process mining, namely 19 times (54,29%). The paper of Ganesha et al. (2017) is an example of where *human health and social work activities* is the focus sector. This research investigates a method for identifying possible efficiency gains in the healthcare industry by using process mining. The authors review how process mining techniques have been implemented in the past and then examine improved implementation strategies by considering elements such as time, cost, and resource use.

Others appeared 8 times (22,86%). It comprises mining and quarrying; electricity, gas, steam and air conditioning supply; construction; wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage; financial and insurance activities; public administration and defence, and compulsory social security; and professional, scientific and technical activities. Since each of these appeared only once, the elements are put together under *Others*.

Table 10. Overview of purpose sectors.

Purpose sector	Publications (in #)	Publications (in %)
P - Education	2	5,71%
C - Manufacturing	3	8,57%
J - Information And Communication	3	8,57%
Q - Human Health And Social Work Activities	19	54,29%
Others	8	22.86%
Total of specific for sector	*35*	*100%*

Evaluation with domain experts

Process mining initiatives cannot be translated into actionable insights without the participation of experts in the field, as concluded by Koorn et al. (2021). The same authors also conclude that a systematic strategy (typically including domain experts) to establishing the accuracy and significance of process mining data is generally absent. However, evaluation of domain experts is an important factor of realising useful outcomes for the industry. There are four possibilities for the evaluation of a domain expert to consider: either an artefact, an insight, both insight and artefact, and no evaluation. An overview can be found in Table 11. No evaluation appeared the most, namely 141 times (86,50%). It comes down to 86,50% of the publications not consulting any domain experts, leaving only 13,50% publications which did seek advice from domain experts.

In terms of *insights*, the examination carried out with domain expert focuses on the generated understandings (i.e. the results of the analysis). There were 13 occurrences of it (7,98%). An example is the article of Cho et al. (2021b). This article presents a systematic technique for developing a resource-oriented transition system model in a semiconductor manufacturing process in order to identify high and poor yielding resource pathways. A transition system is a basic and simple process modelling notation, it is often used in process mining to get relevant findings that summarise log behaviour based on abstraction approaches. The obtained model is interpreted via a conversation with domain experts to determine the yield's underlying reasons. Thus, it recognises which flows have an effect on yield and attempts to determine their causes.

The emphasis on the *artefact* appeared 5 times (3,07%), indicating that domain experts provide comments on the preparation and procedure, such as the method. An example paper is Martinez-Millana et al. (2019). In an operating rooms of a hospital equipped with a real-time location system, the authors plan to analyse the desired features of a process mining-based dashboard. The dashboard enables the identification and improvement of patient flows based on the location data of patients under treatment. The authors consult domain experts to elicit the required features of the process mining-based dashboard.

Lastly, both *artefact and insights* could be combined, although this only emerged 4 times (2,45%). For example, the article of Pika et al. (2017) consulted domain experts with an artefact focus for the data cleaning process, and also for insights into the results. They propose a framework that extracts descriptive information on resource skills, use, preferences, productivity, and collaboration. Their framework also analyses resource behaviours and results. Furthermore, it evaluates resource productivity, tracks changes over time, and compares it to other resources' productivity.

Table 11. Overview of evaluation focus (classification by Koorn et al., 2021).

Evaluation focus	Publications (in #)	Publications (in %)
No evaluation	141	86,50%
Insights	13	7,98%
Artefact	5	3,07%
Artefact and insights	4	2,45%
Total	*163*	*100%*

Seven evaluation methods were sought after in the 163 publications, more specifically manual annotations, experiments, interviews, focus groups, surveys, workshops, and undefined discussions. Manual annotations, experiments, interviews, and focus groups are omitted from Table 12, as they were not discovered in the publications.

An example article that used a *workshop* is Schönig et al. (2016b). They provide a framework for process mining in order to find resource-aware process models. To verify the model, a workshop was carried out with a total of eight process participants, who were employees of a university and who together represented all of the organisational groupings that were engaged in the study. Thus they generated insights from the workshop with domain experts.

The article of Pika et al. (2017) that was mentioned earlier uses two evaluation methods, that is why the total of Table 9 is 164* instead of 163. Pika et al. (2017) used domain experts to validate the data cleaning process in an *undefined discussion*, as well as a *survey* to substantiate the results.

Table 12. Overview of evaluation methods (classification by Koorn et al., 2021).

Evaluation method	Appearance (in #)	Appearance (in %)
Workshops	1	0,61%
Surveys	3	1,83%
Undefined discussions	19	11,59%
No evaluation	141	85,98%
Total	*164**	*100%*

5. Discussion

Since the inception of process mining several years ago, numerous algorithms, tools, and strategies have been proposed. This literature study contributes to the field by compiling a collection of relevant, insightful, and rigorous studies addressing the resource perspective in process mining. Additionally, some significant observations have been discovered as a result of data analysis of 163 publications. The material has been categorised into four foci (i.e. general descriptives, process mining, resource perspective, industry) and tagged based on a variety of 10 topics (e.g. perspectives, use cases, purpose sectors). These results are put against a background of current (industry) trends and resource perspective and process mining trends. More specifically, the discussion talks about general trends, the evaluation with domain experts, sector potential, industry 4.0, and advanced analytics. Limitations are also discussed at the end of this section.

First, there has been a significant increase in the number of publications, which demonstrates that more and more people are becoming interested in the topic. Nevertheless, this should be contextualised within the expanding interest in process mining in general (van der Aalst, 2020). Researchers are also mainly focusing on method development and application, which means that they are investing techniques and instantly testing them out. While this generally can be seen as positive, it is difficult to keep up with all of the many technologies and applications that are now available. There is a requirement for a systematic review that gives the latest advances (e.g. existing algorithms), and this requirement may provide a focus for study in the future. To obtain a more in-depth overview of the resource viewpoint in process mining, cross-referencing the data and combining the subjects that were covered in this thesis are two additional recommendations for future study that should be taken into consideration.

Second, looking at the literature from an industrial lens indicates that there is a significant lack of utilisation of domain expertise. Only 13,5% of the publications make use of subject matter experts to either comment on the artefact, provide insights, or do both. That is a rather low standard. According to the findings presented by Koorn et al. (2021), process mining initiatives cannot be transformed into actionable insights without the support of domain experts. In addition, they claim that in order to show the accuracy and significance of process mining, a methodical approach that includes the participation of domain experts is necessary. As a consequence of this, there is a perceived requirement for more constant participation from domain experts in process mining initiatives in order to achieve higher-quality results in projects. When we zoom in even more on the findings of this thesis, it is observed that even if there is evaluation with domain experts, it is mostly to interpret the findings (7,98%). When it comes to providing input on the process of the project (e.g. the methodology), domain experts are even less involved (2,45%). It is important to bridge the gap between researchers and domain specialists in order to obtain true insights into the industry and business value of the resource perspective in process mining.

Third, the purpose sectors of the articles were not particularly diverse; the majority of the study focused on human health and social work activities (54,29%). This indicates that healthcare-related topics accounted for more than half of the research conducted by the purpose sector. According to De Roock and Martin (2022), there has been an increase in research interest in process mining. This industry is considered to be important for a number of different reasons, e.g. the enormous amounts of data that are being generated by care processes (Ghasemi and Amyot, 2016), or the increasing pressure that is being placed on hospitals to operate as efficiently as possible while incurring the least amount of costs as possible (Stefanini et al., 2020). Additionally, from a resource viewpoint in process mining, the sector may be popular since it is a labor-intensive industry. It is justified that this industry is receiving so much attention, but there is enormous potential in a variety of other industries as well. From a resource standpoint, virtually every labor-intensive industry stands to profit tremendously from process mining from the resource perspective. Retail, construction, and education are examples of such industries.

Fourth, Industry 4.0 is upcoming. Information and communication technologies are slowly but surely making their way into every aspect of the industrial and manufacturing processes, which is hastening the accumulation of vast volumes of industrial data (Raptis et al., 2019). This leaves an immense quantity of data that may be utilised for process mining in general, and this most certainly includes data on the resources operating in manufacturing. An organisation will require a powerful HR strategy in order to be successful in navigating the challenges posed by the transition to Industry 4.0. The bulk of HR tasks are going to be automated thanks to developing technologies like the Internet of Things, Big Data, and artificial intelligence, this will result in HR departments that are more efficient and smaller in size (Sivathanu and Pillai, 2018). Process mining from a resource-oriented point of view is one of the methods that may be utilised to cope with these massive volumes of data. Numerous HR-related insights are capable of being obtained by utilising use cases that are currently commonplace in the industry, such as resource assignment (24%), resource behaviour and performance quantification (22%), and social network identification (19%).

Fifth, advanced prediction methods are necessary to methodically turn data into knowledge in order to give an explanation for uncertainty. This is especially true given the numerous technology trends that exist these days (e.g. Industry 4.0, datafication of the world, etc.). The application of increasingly complex prediction algorithms allows for "informed" decision-making (Lee et al., 2014). The number of predictive (6,13%) and prescriptive (6,75%) assessments is currently minimal. It is clear that the study focus is still on descriptive process mining (87.12%) and process discovery (93,25%). This means that there are several methods to uncover and characterise current business occurrences. However, a lot of potential is lost due to a lack of attention on the other components. In addition to predictive and prescriptive emphases, several works (Song and van der Aalst, 2008; Huang et al., 2012) have emphasised that conformance (12,88%) requires further attention. The resource perspective literature has yet to grow to include more diverse studies from a process mining approach. Another step further would be enhancement (15,95%). Despite an increase in conformance and enhancement focuses (van der Aalst, 2020), additional research is required. The maturity of the resource perspective in process mining technology will be significantly enhanced and accelerated by focusing on these concerns.

The findings of this thesis have to be seen in the light of some limitations. First, the methodology's research team had to make a number of decisions in order to establish the literature search strategy, which included selecting search keywords. As a result, there is no guarantee that every publication relating to the resource perspective in process mining has been recognised. However, transparency in technique and search strategy contributes to the reproducibility and validity of this thesis. Second, because authors can only analyse publications that are available within the searching time frame, there is an element of publication bias present before the search begins. The inclusion and exclusion criteria are expressly mentioned to control this preconception. Third, one could argue that the selection of the lenses and topics was arbitrary. The topics are prevalent and accepted subjects within the process mining community. Additionally, regarding the lenses, one of the aims of this thesis is to establish a foundation for future work and to give a preliminary structure. Fourth, despite the fact that grey literature (e.g., reports) may be relevant or have added value, they are deliberately not included in the thesis at hand. Because it has not been subjected to peer review, grey literature is not taken into consideration.

6. Conclusion

Process mining studies data from information systems in order to discover, monitor, and optimise processes as they exist. A process is a sequence of actions conducted in order to attain an objective. These actions are performed by an employee, also known as a resource. The resource perspective is one of the different views that may be examined during process mining activities. This thesis gives an analysis of relevant literature on the resource perspective in the process mining study domain, which comprised 163 papers. This is a first contribution to studying the literature on the resource perspective, which opens prospects for further research.

Four lenses were used to examine the literature: general descriptives, process mining lens, resource perspective lens, and industry lens. There are a total of ten subjects contained within each of the ten foci. The most significant findings are described as follows. Regarding general descriptors, there is an upward tendency in the publication of papers, with method development and application being the bulk of paper focus. Regarding the process mining lens, descriptive analysis, discovery type, and the control-flow perspective are the most often discussed subjects in the present literature. The resource perspective lens reveals that the individual resource and the single department of a single organisation are the most typical scopes. The most common use case is resource assignment. Regarding the industry lens, it is evident that the majority of papers are intended for a general purpose rather than a specific industry, and that domain specialists are rarely consulted.

Based on the findings, there are some recommendations for further research. To begin, future research should broaden the current literature study by incorporating more classification attributes, such as algorithms, and by combining data on the themes covered in this literature review to undertake a more in-depth analysis. Second, domain experts should be consulted on a more regular basis, since more qualitative results and research papers in general can come from it. Third, any (labour-intensive) business can gain from using process mining from the resource perspective. Especially since resources are the core of process execution. Thus it may be interesting to identify such specific industries and make case studies out of them. Fourth, building on the third recommendation, Industry 4.0 is on the horizon. This means there are opportunities for in-depth inquiry in the manufacturing sector thanks to abundant amounts of data. Fifth, the focus of research in process mining on the resource perspective should broaden in terms of predictive and prescriptive analysis, as well as conformance and enhancement analysis.

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8. Appendix

8.1. Complete list of used literature for the analysis

Table 13. Complete list of literature used for the analysis.

#	Short reference
1	(Abdelkafi and Bouzguenda, 2010)
2	(Abdelkafi and Bouzguenda, 2015)
3	(Abdelkafi et al., 2012)
4	(Agostinelli et al., 2020)
5	(Ahn and Kim, 2020)
6	(Allen and Tilbury, 2012)
7	(Aloini et al., 2020)
8	(Alvarez et al., 2018)
9	(Appice and Malerba, 2015)
10	(Appice et al., 2016)
11	(Appice, 2018)
12	(Arias et al., 2016a)
13	(Arias et al., 2016b)
14	(Arias et al., 2018a)
15	(Arias et al., 2018b)
16	(Bellaaj Elloumi et al., 2020)
17	(Bhogal and Garg, 2020)
18	(Bidar et al., 2019)
19	(Bose and van der Aalst, 2013)
20	(Boulmakoul and Besri, 2013)
21	(Bouzguenda and Abdelkafi, 2015)
22	(Bozkaya et al., 2009)
23	(Burattin et al., 2013)
24	(C. Liu et al., 2020)
25	(Cabanillas et al., 2018)
26	(Cabanillas et al., 2020)
27	(Cabanillas, 2016)
28	(Caron et al., 2014)
29	(Carrera and Jung, 2015)
30	(Cho et al., 2021a)
31	(Cho et al., 2021b)
32	(de Leoni et al., 2012)
33	(de Murillas et al., 2017)
34	(De Weerdt et al., 2015)
35	(Delcoucq et al., 2020)
36	(Delgado and Calegari, 2020)
37	(Deokar and Tao, 2021)
38	(Diamantini et al., 2016)
39	(Djedović et al., 2016)
40	(Djedovic et al., 2018)
41	(Dustdar and Hoffmann, 2007)
42	(Ebrahim and Golpayegani, 2021)
43	(Elleuch et al., 2020)
44	(Ellis et al., 2006)
45	(Estrada-Torres et al., 2021)
46	(Ferreira and Alves, 2012)
47	(Firouzian et al., 2019)
48	(Ganesha et al., 2017)
49	(Gao et al., 2009)
50	(Ghazanfari et al., 2010)
51	(Gupta et al., 2014)
52	(Gupta, 2014)
53	(Hanachi et al., 2012)
54	(Havur and Cabanillas, 2019)
55	(He et al., 2019)
56	(Heo et al., 2018)
57	(Hidayat et al., 2016)
58	(Huang et al., 2011)
59	(Huang et al., 2012)
60	(J. Park et al., 2016)
61	(J. Park et al., 2018)
62	(Jafari et al., 2020)
63	(Jin et al., 2007)
64	(Kamal et al., 2017)
65	(Koosawad et al., 2018)
66	(Kouhestani and Nik-Bakht, 2020)
67	(Krutanard et al., 2015)
68	(Lai and Liu, 2008)
69	(Larsen and Villadsen, 2017)
70	(Lee et al., 2019)
71	(Leitner et al., 2013)
72	(Li et al., 2011)
73	(Low et al., 2017)
74	(Ly et al., 2006)
75	(M. Park et al., 2016)

76	(M'hand et al., 2021)
77	(Mannhardt et al., 2016)
78	(Mans et al., 2008a)
79	(Mans et al., 2008b)
80	(Martin et al., 2015)
81	(Martin et al., 2016)
82	(Martin et al., 2017)
83	(Martin et al., 2020)
84	(Martin et al., 2021)
85	(Martinez-Millana et al., 2019)
86	(Matzner and Scholta, 2014)
87	(Mesabbah et al., 2019)
88	(Nakatumba and van der Aalst, 2010)
89	(Nakatumba et al., 2012)
90	(Nguyen et al., 2018)
91	(Ni et al., 2011)
92	(Obregon et al., 2013)
93	(Ogunbiyi et al., 2021)
94	(Pan and Zhang, 2021)
95	(Park and Song, 2019)
96	(Pika and Wynn, 2021)
97	(Pika et al., 2014)
98	(Pika et al., 2017)
99	(Pinto et al., 2015)
100	(Porouhan and Premchaiswadi, 2015)
101	(Porouhan and Premchaiswadi, 2017)
102	(Premchaiswadi and Porouhan, 2015)
103	(Prokofyeva et al., 2020)
104	(Raitubu et al., 2019)
105	(Rasyidi, 2017)
106	(Rattanavayakorn and Premchaiswadi, 2015)
107	(Reijers et al., 2007)
108	(Rembert, 2006)
109	(Reungrungsee et al., 2012)
110	(Rozinat et al., 2009)
111	(Saelim et al., 2016)
112	(Saito, 2019)
113	(Sakchaikun et al., 2018)
114	(Schönig et al., 2012)
115	(Schönig et al., 2015a)
116	(Schönig et al., 2015b)
117	(Schönig et al., 2016a)
118	(Schönig et al., 2016b)
119	(Schönig et al., 2018)
120	(Sellami et al., 2012)
121	(Senderovich et al., 2016a)
122	(Senderovich et al., 2016b)
123	(Sikal et al., 2019)
124	(Sitova and Pecerska, 2020)
125	(Slaninová et al., 2015)
126	(Soboleva and Tushkanova, 2020)
127	(Song and van der Aalst, 2008)
128	(Sophia and Sarno, 2018a)
129	(Sophia and Sarno, 2018b)
130	(Sophia and Sarno, 2019)
131	(Stefanini et al., 2017)
132	(Stefanini et al., 2020)
133	(Stuit and Wortmann, 2012)
134	(Sun et al., 2020)
135	(Suriadi et al., 2017)
136	(Swennen et al., 2016)
137	(T. Liu et al., 2008)
138	(T. Liu et al., 2012)
139	(Tamburis and Esposito, 2020)
140	(Tang and Matzner, 2020)
141	(Thomas et al., 2017)
142	(van der Aalst and Song, 2004)
143	(Wang et al., 2016)
144	(Wang et al., 2017)
145	(Wongvigran and Premchaiswadi, 2015)
146	(Y. Liu et al., 2012)
147	(Y.B. Liu et al., 2007)
148	(Y.B. Liu et al., 2008)
149	(Y.B. Liu et al., 2011)
150	(Yaghoubi and Zahedi, 2016)
151	(Yahya, 2014)
152	(Yang et al., 2018)
153	(Ye et al., 2018)
154	(Zeng et al., 2013)
155	(Zhao and Zhao, 2014)
156	(Zhao et al., 2015)
157	(Zhao et al., 2016)
158	(Zhao et al., 2019)
159	(Zhao et al., 2020)
160	(Zhou and Piramuthu, 2010a)
161	(Zhou and Piramuthu, 2010b)
162	(Zhou et al., 2020)
163	(Zhu et al., 2017)

8.2. Complete table of process mining perspectives

Table 14. Complete table of process mining perspectives by short reference.

#	Discovery
1	(Abdelkafi and Bouzguenda, 2010)
2	(Abdelkafi and Bouzguenda, 2015)
3	(Abdelkafi et al., 2012)
4	(Agostinelli et al., 2020)
5	(Ahn and Kim, 2020)
6	(Allen and Tilbury, 2012)
7	(Aloini et al., 2020)
8	(Alvarez et al., 2018)
9	(Appice and Malerba, 2015)
10	(Appice et al., 2016)
11	(Appice, 2018)
12	(Arias et al., 2016a)
13	(Arias et al., 2016b)
14	(Arias et al., 2018a)
15	(Bhogal and Garg, 2020)
16	(Bidar et al., 2019)
17	(Bose and van der Aalst, 2013)
18	(Boulmakoul and Besri, 2013)
19	(Bouzguenda and Abdelkafi, 2015)
20	(Bozkaya et al., 2009)
21	(Burattin et al., 2013)
22	(C. Liu et al., 2020)
23	(Cabanillas et al., 2018)
24	(Cabanillas et al., 2020)
25	(Cabanillas, 2016)
26	(Caron et al., 2014)
27	(Carrera and Jung, 2015)
28	(Cho et al., 2021a)
29	(Cho et al., 2021b)
30	(De Weerdt et al., 2015)
31	(Delcoucq et al., 2020)
32	(Delgado and Calegari, 2020)
33	(Deokar and Tao, 2021)
34	(Diamantini et al., 2016)
35	(Djedović et al., 2016)
36	(Djedovic et al., 2018)
37	(Dustdar and Hoffmann, 2007)
38	(Ebrahim and Golpayegani, 2021)
39	(Elleuch et al., 2020)
40	(Ellis et al., 2006)
41	(Estrada-Torres et al., 2021)
42	(Ferreira and Alves, 2012)
43	(Ganesha et al., 2017)
44	(Gao et al., 2009)
45	(Ghazanfari et al., 2010)
46	(Gupta et al., 2014)
47	(Gupta, 2014)
48	(Hanachi et al., 2012)
49	(Havur and Cabanillas, 2019)
50	(He et al., 2019)
51	(Heo et al., 2018)
52	(Hidayat et al., 2016)
53	(Huang et al., 2011)
54	(Huang et al., 2012)
55	(J. Park et al., 2016)
56	(J. Park et al., 2018)
57	(Jafari et al., 2020)
58	(Jin et al., 2007)
59	(Kamal et al., 2017)
60	(Koosawad et al., 2018)
61	(Kouhestani and Nik-Bakht, 2020)
62	(Krutanard et al., 2015)
63	(Lai and Liu, 2008)
64	(Larsen and Villadsen, 2017)
65	(Lee et al., 2019)
66	(Leitner et al., 2013)
67	(Li et al., 2011)
68	(Low et al., 2017)
69	(Ly et al., 2006)
70	(M. Park et al., 2016)
71	(M'hand et al., 2021)
72	(Mans et al., 2008a)
73	(Mans et al., 2008b)
74	(Martin et al., 2015)
75	(Martin et al., 2016)
76	(Martin et al., 2017)
77	(Martin et al., 2020)
78	(Martin et al., 2021)
79	(Martinez-Millana et al., 2019)
80	(Matzner and Scholta, 2014)
81	(Mesabbah et al., 2019)
82	(Nakatumba and van der Aalst, 2010)
83	(Nakatumba et al., 2012)
84	(Nguyen et al., 2018)

85	(Ni et al., 2011)
86	(Obregon et al., 2013)
87	(Ogunbiyi et al., 2021)
88	(Pan and Zhang, 2021)
89	(Pika and Wynn, 2021)
90	(Pika et al., 2014)
91	(Pika et al., 2017)
92	(Pinto et al., 2015)
93	(Porouhan and Premchaiswadi, 2015)
94	(Premchaiswadi and Porouhan, 2015)
95	(Prokofyeva et al., 2020)
96	(Raitubu et al., 2019)
97	(Rasyidi, 2017)
98	(Rattanavayakorn and Premchaiswadi, 2015)
99	(Reijers et al., 2007)
100	(Rembert, 2006)
101	(Reungrungsee et al., 2012)
102	(Rozinat et al., 2009)
103	(Saelim et al., 2016)
104	(Saito, 2019)
105	(Sakchaikun et al., 2018)
106	(Schönig et al., 2012)
107	(Schönig et al., 2015a)
108	(Schönig et al., 2015b)
109	(Schönig et al., 2016a)
110	(Schönig et al., 2016b)
111	(Schönig et al., 2018)
112	(Sellami et al., 2012)
113	(Senderovich et al., 2016a)
114	(Sikal et al., 2019)
115	(Sitova and Pecerska, 2020)
116	(Slaninová et al., 2015)
117	(Soboleva and Tushkanova, 2020)
118	(Song and van der Aalst, 2008)
119	(Sophia and Sarno, 2018a)
120	(Sophia and Sarno, 2018b)
121	(Sophia and Sarno, 2019)
122	(Stefanini et al., 2017)
123	(Stuit and Wortmann, 2012)
124	(Sun et al., 2020)
125	(Suriadi et al., 2017)
126	(Swennen et al., 2016)
127	(T. Liu et al., 2008)
128	(T. Liu et al., 2012)
129	(Tamburis and Esposito, 2020)
130	(Tang and Matzner, 2020)
131	(Thomas et al., 2017)
132	(van der Aalst and Song, 2004)
133	(Wang et al., 2016)
134	(Wang et al., 2017)
135	(Wongvigran and Premchaiswadi, 2015)
136	(Y. Liu et al., 2012)
137	(Y.B. Liu et al., 2007)
138	(Y.B. Liu et al., 2008)
139	(Y.B. Liu et al., 2011)
140	(Yaghoubi and Zahedi, 2016)
141	(Yahya, 2014)
142	(Yang et al., 2018)
143	(Ye et al., 2018)
144	(Zeng et al., 2013)
145	(Zhao and Zhao, 2014)
146	(Zhao et al., 2015)
147	(Zhao et al., 2016)
148	(Zhao et al., 2020)
149	(Zhou and Piramuthu, 2010a)
150	(Zhou and Piramuthu, 2010b)
151	(Zhou et al., 2020)
152	(Zhu et al., 2017)

#	**Conformance**
153	(Boulmakoul and Besri, 2013)
154	(Cabanillas et al., 2018)
155	(Cabanillas et al., 2020)
156	(Caron et al., 2014)
157	(de Leoni et al., 2012)
158	(De Weerdt et al., 2015)
159	(Ganesha et al., 2017)
160	(Gupta, 2014)
161	(Hidayat et al., 2016)
162	(Kouhestani and Nik-Bakht, 2020)
163	(Lai and Liu, 2008)
164	(Mannhardt et al., 2016)
165	(Pan and Zhang, 2021)
166	(Premchaiswadi and Porouhan, 2015)
167	(Saelim et al., 2016)
168	(Senderovich et al., 2016b)
169	(Wang et al., 2016)
170	(Wongvigran and Premchaiswadi, 2015)
171	(Y. Liu et al., 2012)

#	Enhancement (continued)
172	(Zhao and Zhao, 2014)
173	(Zhu et al., 2017)

#	Enhancement
174	(Arias et al., 2016b)
175	(Bellaaj Elloumi et al., 2020)
176	(Cabanillas et al., 2018)
177	(de Murillas et al., 2017)
178	(Firouzian et al., 2019)
179	(Ganesha et al., 2017)
180	(Gupta, 2014)
181	(Hidayat et al., 2016)
182	(Jafari et al., 2020)
183	(Lai and Liu, 2008)
184	(Low et al., 2017)
185	(Martinez-Millana et al., 2019)
186	(Obregon et al., 2013)
187	(Pan and Zhang, 2021)
188	(Park and Song, 2019)
189	(Porouhan and Premchaiswadi, 2015)
190	(Porouhan and Premchaiswadi, 2017)
191	(Saelim et al., 2016)
192	(Senderovich et al., 2016b)
193	(Stefanini et al., 2020)
194	(Wang et al., 2016)
195	(Wang et al., 2017)
196	(Y. Liu et al., 2012)
197	(Zhao and Zhao, 2014)
198	(Zhao et al., 2015)
199	(Zhao et al., 2019)

8.3. Complete table of resource scope types

Table 15. Complete table of resource scope types by short reference.

#	Not assigned
1	(de Murillas et al., 2017)
2	(De Weerdt et al., 2015)
3	(He et al., 2019)
4	(Mannhardt et al., 2016)
5	(Matzner and Scholta, 2014)

#	Individual resource
6	(Abdelkafi et al., 2012)
7	(Agostinelli et al., 2020)
8	(Allen and Tilbury, 2012)
9	(Bhogal and Garg, 2020)
10	(Bose and van der Aalst, 2013)
11	(Boulmakoul and Besri, 2013)
12	(Bouzguenda and Abdelkafi, 2015)
13	(Bozkaya et al., 2009)
14	(Cabanillas et al., 2018)
15	(Cabanillas et al., 2020)
16	(Cabanillas, 2016)
17	(Caron et al., 2014)
18	(Carrera and Jung, 2015)
19	(Cho et al., 2021b)
20	(de Leoni et al., 2012)
21	(Djedović et al., 2016)
22	(Djedovic et al., 2018)
23	(Ellis et al., 2006)
24	(Estrada-Torres et al., 2021)
25	(Firouzian et al., 2019)
26	(Gupta, 2014)
27	(Huang et al., 2011)
28	(Huang et al., 2012)
29	(Koosawad et al., 2018)
30	(Kouhestani and Nik-Bakht, 2020)
31	(Larsen and Villadsen, 2017)
32	(Lee et al., 2019)
33	(Leitner et al., 2013)
34	(Low et al., 2017)
35	(Ly et al., 2006)
36	(Mans et al., 2008a)
37	(Martin et al., 2015)
38	(Martin et al., 2016)
39	(Martin et al., 2017)
40	(Martin et al., 2020)
41	(Martin et al., 2021)
42	(Martinez-Millana et al., 2019)
43	(Mesabbah et al., 2019)
44	(Nakatumba and van der Aalst, 2010)
45	(Nakatumba et al., 2012)
46	(Nguyen et al., 2018)
47	(Ni et al., 2011)
48	(Obregon et al., 2013)
49	(Ogunbiyi et al., 2021)
50	(Pan and Zhang, 2021)

51	(Pika and Wynn, 2021)
52	(Pika et al., 2014)
53	(Porouhan and Premchaiswadi, 2017)
54	(Prokofyeva et al., 2020)
55	(Rasyidi, 2017)
56	(Rembert, 2006)
57	(Rozinat et al., 2009)
58	(Saelim et al., 2016)
59	(Saito, 2019)
60	(Sakchaikun et al., 2018)
61	(Schönig et al., 2012)
62	(Schönig et al., 2015b)
63	(Schönig et al., 2016b)
64	(Senderovich et al., 2016a)
65	(Senderovich et al., 2016b)
66	(Sikal et al., 2019)
67	(Sitova and Pecerska, 2020)
68	(Slaninová et al., 2015)
69	(Sophia and Sarno, 2018a)
70	(Sophia and Sarno, 2018b)
71	(Sophia and Sarno, 2019)
72	(Stefanini et al., 2017)
73	(Stefanini et al., 2020)
74	(Stuit and Wortmann, 2012)
75	(Suriadi et al., 2017)
76	(Swennen et al., 2016)
77	(Tamburis and Esposito, 2020)
78	(Tang and Matzner, 2020)
79	(Thomas et al., 2017)
80	(Wang et al., 2017)
81	(Y.B. Liu et al., 2007)
82	(Y.B. Liu et al., 2008)
83	(Yang et al., 2018)
84	(Zeng et al., 2013)
85	(Zhao et al., 2015)
86	(Zhou and Piramuthu, 2010a)
87	(Zhou et al., 2020)
88	(Zhu et al., 2017)
#	**Team**
89	(Abdelkafi and Bouzguenda, 2010)
90	(Abdelkafi and Bouzguenda, 2015)
91	(Ahn and Kim, 2020)
92	(Aloini et al., 2020)
93	(Alvarez et al., 2018)
94	(Appice and Malerba, 2015)
95	(Appice et al., 2016)
96	(Appice, 2018)
97	(Arias et al., 2016a)
98	(Arias et al., 2016b)
99	(Arias et al., 2018a)
100	(Arias et al., 2018b)
101	(Bellaaj Elloumi et al., 2020)
102	(Bidar et al., 2019)
103	(Burattin et al., 2013)
104	(C. Liu et al., 2020)
105	(Cho et al., 2021a)
106	(Delcoucq et al., 2020)
107	(Delgado and Calegari, 2020)
108	(Deokar and Tao, 2021)
109	(Diamantini et al., 2016)
110	(Dustdar and Hoffmann, 2007)
111	(Ebrahim and Golpayegani, 2021)
112	(Elleuch et al., 2020)
113	(Ferreira and Alves, 2012)
114	(Ganesha et al., 2017)
115	(Gao et al., 2009)
116	(Ghazanfari et al., 2010)
117	(Gupta et al., 2014)
118	(Hanachi et al., 2012)
119	(Havur and Cabanillas, 2019)
120	(Heo et al., 2018)
121	(Hidayat et al., 2016)
122	(J. Park et al., 2016)
123	(J. Park et al., 2018)
124	(Jafari et al., 2020)
125	(Jin et al., 2007)
126	(Kamal et al., 2017)
127	(Krutanard et al., 2015)
128	(Lai and Liu, 2008)
129	(Li et al., 2011)
130	(M. Park et al., 2016)
131	(M'hand et al., 2021)
132	(Mans et al., 2008b)
133	(Park and Song, 2019)
134	(Pika et al., 2017)
135	(Pinto et al., 2015)
136	(Porouhan and Premchaiswadi, 2015)
137	(Premchaiswadi and Porouhan, 2015)
138	(Raitubu et al., 2019)
139	(Rattanavayakorn and Premchaiswadi, 2015)
140	(Reijers et al., 2007)

141	(Reungrungsee et al., 2012)
142	(Schönig et al., 2015a)
143	(Schönig et al., 2016a)
144	(Schönig et al., 2018)
145	(Sellami et al., 2012)
146	(Soboleva and Tushkanova, 2020)
147	(Song and van der Aalst, 2008)
148	(Sun et al., 2020)
149	(T. Liu et al., 2008)
150	(T. Liu et al., 2012)
151	(van der Aalst and Song, 2004)
152	(Wang et al., 2016)
153	(Wongvigran and Premchaiswadi, 2015)
154	(Y. Liu et al., 2012)
155	(Y.B. Liu et al., 2011)
156	(Yaghoubi and Zahedi, 2016)
157	(Yahya, 2014)
158	(Ye et al., 2018)
159	(Zhao and Zhao, 2014)
160	(Zhao et al., 2016)
161	(Zhao et al., 2019)
162	(Zhao et al., 2020)
163	(Zhou and Piramuthu, 2010b)

8.4. Complete table of organisational scope types

Table 16. Complete overview of organisational scope types by short reference.

#	Not assigned
1	(Burattin et al., 2013)
2	(de Murillas et al., 2017)
3	(De Weerdt et al., 2015)
4	(Diamantini et al., 2016)
5	(Mannhardt et al., 2016)
6	(Ni et al., 2011)
7	(Rozinat et al., 2009)
8	(Sikal et al., 2019)
#	**Several departments of single organisation**
9	(Appice, 2018)
10	(Bhogal and Garg, 2020)
11	(Deokar and Tao, 2021)
12	(Hanachi et al., 2012)
13	(Kamal et al., 2017)
14	(Kouhestani and Nik-Bakht, 2020)
15	(Lai and Liu, 2008)
16	(M. Park et al., 2016)
17	(Mesabbah et al., 2019)
18	(Pinto et al., 2015)
19	(Rattanavayakorn and Premchaiswadi, 2015)
20	(Reijers et al., 2007)
21	(Saito, 2019)
22	(Song and van der Aalst, 2008)
23	(Wang et al., 2016)
24	(Y. Liu et al., 2012)
#	**Several organisations**
25	(C. Liu et al., 2020)
26	(Delgado and Calegari, 2020)
27	(Zeng et al., 2013)
#	**Single department of single organisation**
28	(Abdelkafi and Bouzguenda, 2010)
29	(Abdelkafi and Bouzguenda, 2015)
30	(Abdelkafi et al., 2012)
31	(Agostinelli et al., 2020)
32	(Ahn and Kim, 2020)
33	(Allen and Tilbury, 2012)
34	(Aloini et al., 2020)
35	(Alvarez et al., 2018)
36	(Appice and Malerba, 2015)
37	(Appice et al., 2016)
38	(Arias et al., 2016a)
39	(Arias et al., 2016b)
40	(Arias et al., 2018a)
41	(Arias et al., 2018b)
42	(Bellaaj Elloumi et al., 2020)
43	(Bidar et al., 2019)
44	(Bose and van der Aalst, 2013)
45	(Boulmakoul and Besri, 2013)
46	(Bouzguenda and Abdelkafi, 2015)
47	(Bozkaya et al., 2009)
48	(Cabanillas et al., 2018)
49	(Cabanillas et al., 2020)
50	(Cabanillas, 2016)
51	(Caron et al., 2014)
52	(Carrera and Jung, 2015)
53	(Cho et al., 2021a)

54 (Cho et al., 2021b)
55 (de Leoni et al., 2012)
56 (Delcoucq et al., 2020)
57 (Djedović et al., 2016)
58 (Djedovic et al., 2018)
59 (Dustdar and Hoffmann, 2007)
60 (Ebrahim and Golpayegani, 2021)
61 (Elleuch et al., 2020)
62 (Ellis et al., 2006)
63 (Estrada-Torres et al., 2021)
64 (Ferreira and Alves, 2012)
65 (Firouzian et al., 2019)
66 (Ganesha et al., 2017)
67 (Gao et al., 2009)
68 (Ghazanfari et al., 2010)
69 (Gupta et al., 2014)
70 (Gupta, 2014)
71 (Havur and Cabanillas, 2019)
72 (He et al., 2019)
73 (Heo et al., 2018)
74 (Hidayat et al., 2016)
75 (Huang et al., 2011)
76 (Huang et al., 2012)
77 (J. Park et al., 2016)
78 (J. Park et al., 2018)
79 (Jafari et al., 2020)
80 (Jin et al., 2007)
81 (Koosawad et al., 2018)
82 (Krutanard et al., 2015)
83 (Larsen and Villadsen, 2017)
84 (Lee et al., 2019)
85 (Leitner et al., 2013)
86 (Li et al., 2011)
87 (Low et al., 2017)
88 (Ly et al., 2006)
89 (M'hand et al., 2021)
90 (Mans et al., 2008a)
91 (Mans et al., 2008b)
92 (Martin et al., 2015)
93 (Martin et al., 2016)
94 (Martin et al., 2017)
95 (Martin et al., 2020)
96 (Martin et al., 2021)
97 (Martinez-Millana et al., 2019)
98 (Matzner and Scholta, 2014)
99 (Nakatumba and van der Aalst, 2010)
100 (Nakatumba et al., 2012)
101 (Nguyen et al., 2018)
102 (Obregon et al., 2013)
103 (Ogunbiyi et al., 2021)
104 (Pan and Zhang, 2021)
105 (Park and Song, 2019)
106 (Pika and Wynn, 2021)
107 (Pika et al., 2014)
108 (Pika et al., 2017)
109 (Porouhan and Premchaiswadi, 2015)
110 (Porouhan and Premchaiswadi, 2017)
111 (Premchaiswadi and Porouhan, 2015)
112 (Prokofyeva et al., 2020)
113 (Raitubu et al., 2019)
114 (Rasyidi, 2017)
115 (Rembert, 2006)
116 (Reungrungsee et al., 2012)
117 (Saelim et al., 2016)
118 (Sakchaikun et al., 2018)
119 (Schönig et al., 2012)
120 (Schönig et al., 2015a)
121 (Schönig et al., 2015b)
122 (Schönig et al., 2016a)
123 (Schönig et al., 2016b)
124 (Schönig et al., 2018)
125 (Sellami et al., 2012)
126 (Senderovich et al., 2016a)
127 (Senderovich et al., 2016b)
128 (Sitova and Pecerska, 2020)
129 (Slaninová et al., 2015)
130 (Soboleva and Tushkanova, 2020)
131 (Sophia and Sarno, 2018a)
132 (Sophia and Sarno, 2018b)
133 (Sophia and Sarno, 2019)
134 (Stefanini et al., 2017)
135 (Stefanini et al., 2020)
136 (Stuit and Wortmann, 2012)
137 (Sun et al., 2020)
138 (Suriadi et al., 2017)
139 (Swennen et al., 2016)
140 (T. Liu et al., 2008)
141 (T. Liu et al., 2012)

142	(Tamburis and Esposito, 2020)
143	(Tang and Matzner, 2020)
144	(Thomas et al., 2017)
145	(van der Aalst and Song, 2004)
146	(Wang et al., 2017)
147	(Wongvigran and Premchaiswadi, 2015)
148	(Y.B. Liu et al., 2007)
149	(Y.B. Liu et al., 2008)
150	(Y.B. Liu et al., 2011)
151	(Yaghoubi and Zahedi, 2016)
152	(Yahya, 2014)
153	(Yang et al., 2018)
154	(Ye et al., 2018)
155	(Zhao and Zhao, 2014)
156	(Zhao et al., 2015)
157	(Zhao et al., 2016)
158	(Zhao et al., 2019)
159	(Zhao et al., 2020)
160	(Zhou and Piramuthu, 2010a)
161	(Zhou and Piramuthu, 2010b)
162	(Zhou et al., 2020)
163	(Zhu et al., 2017)

8.5. Complete table of use case types

Table 17. Complete overview of use case type by short reference.

#	Conformance and anomaly analysis
1	(Allen and Tilbury, 2012)
2	(Boulmakoul and Besri, 2013)
3	(Cabanillas et al., 2020)
4	(Caron et al., 2014)
5	(de Leoni et al., 2012)
6	(Ebrahim and Golpayegani, 2021)
7	(Heo et al., 2018)
8	(Kouhestani and Nik-Bakht, 2020)
9	(Pan and Zhang, 2021)
10	(Premchaiswadi and Porouhan, 2015)
11	(Raitubu et al., 2019)
12	(Saelim et al., 2016)
13	(Senderovich et al., 2016a)
14	(Senderovich et al., 2016b)
15	(Sitova and Pecerska, 2020)
16	(Tamburis and Esposito, 2020)
17	(Wongvigran and Premchaiswadi, 2015)
18	(Zhu et al., 2017)
#	**Control-flow discovery**
19	(Abdelkafi and Bouzguenda, 2010)
20	(Abdelkafi and Bouzguenda, 2015)
21	(Allen and Tilbury, 2012)
22	(Bhogal and Garg, 2020)
23	(Bidar et al., 2019)
24	(Bose and van der Aalst, 2013)
25	(Bouzguenda and Abdelkafi, 2015)
26	(Bozkaya et al., 2009)
27	(C. Liu et al., 2020)
28	(Cabanillas et al., 2018)
29	(Cabanillas et al., 2020)
30	(Cabanillas, 2016)
31	(Deokar and Tao, 2021)
32	(Ghazanfari et al., 2010)
33	(Mannhardt et al., 2016)
34	(Mans et al., 2008a)
35	(Mans et al., 2008b)
36	(Martin et al., 2016)
37	(Martin et al., 2020)
38	(Martinez-Millana et al., 2019)
39	(Nguyen et al., 2018)
40	(Ni et al., 2011)
41	(Pinto et al., 2015)
42	(Premchaiswadi and Porouhan, 2015)
43	(Rembert, 2006)
44	(Rozinat et al., 2009)
45	(Saito, 2019)
46	(Schönig et al., 2015a)
47	(Schönig et al., 2015b)
48	(Stuit and Wortmann, 2012)
49	(Tamburis and Esposito, 2020)
#	**Resource assignment**
50	(Abdelkafi et al., 2012)
51	(Appice and Malerba, 2015)
52	(Arias et al., 2016a)
53	(Arias et al., 2016b)
54	(Arias et al., 2018a)
55	(Arias et al., 2018b)
56	(Bellaaj Elloumi et al., 2020)

57	(Bidar et al., 2019)
58	(Cabanillas, 2016)
59	(Caron et al., 2014)
60	(Carrera and Jung, 2015)
61	(de Murillas et al., 2017)
62	(Deokar and Tao, 2021)
63	(Djedović et al., 2016)
64	(Djedovic et al., 2018)
65	(Ellis et al., 2006)
66	(Firouzian et al., 2019)
67	(Gupta, 2014)
68	(Havur and Cabanillas, 2019)
69	(Heo et al., 2018)
70	(Huang et al., 2011)
71	(Larsen and Villadsen, 2017)
72	(Lee et al., 2019)
73	(Low et al., 2017)
74	(Ly et al., 2006)
75	(Matzner and Scholta, 2014)
76	(Mesabbah et al., 2019)
77	(Park and Song, 2019)
78	(Pika and Wynn, 2021)
79	(Prokofyeva et al., 2020)
80	(Schönig et al., 2012)
81	(Schönig et al., 2016a)
82	(Schönig et al., 2016b)
83	(Senderovich et al., 2016b)
84	(Sikal et al., 2019)
85	(Stefanini et al., 2017)
86	(Stefanini et al., 2020)
87	(T. Liu et al., 2008)
88	(T. Liu et al., 2012)
89	(Tamburis and Esposito, 2020)
90	(Y. Liu et al., 2012)
91	(Y.B. Liu et al., 2007)
92	(Y.B. Liu et al., 2008)
93	(Y.B. Liu et al., 2011)
94	(Yaghoubi and Zahedi, 2016)
95	(Yahya, 2014)
96	(Zhao and Zhao, 2014)
97	(Zhao et al., 2015)
98	(Zhao et al., 2016)
99	(Zhou and Piramuthu, 2010a)
100	(Zhou and Piramuthu, 2010b)
#	**Resource behaviour and performance quantification**
101	(Agostinelli et al., 2020)
102	(Ahn and Kim, 2020)
103	(Boulmakoul and Besri, 2013)
104	(Bozkaya et al., 2009)
105	(Burattin et al., 2013)
106	(Caron et al., 2014)
107	(Cho et al., 2021a)
108	(Cho et al., 2021b)
109	(Delcoucq et al., 2020)
110	(Deokar and Tao, 2021)
111	(Diamantini et al., 2016)
112	(Elleuch et al., 2020)
113	(Ganesha et al., 2017)
114	(Huang et al., 2012)
115	(J. Park et al., 2018)
116	(Koosawad et al., 2018)
117	(Lai and Liu, 2008)
118	(Li et al., 2011)
119	(Martin et al., 2015)
120	(Matzner and Scholta, 2014)
121	(Nakatumba and van der Aalst, 2010)
122	(Nakatumba et al., 2012)
123	(Obregon et al., 2013)
124	(Pan and Zhang, 2021)
125	(Pika et al., 2014)
126	(Pika et al., 2017)
127	(Porouhan and Premchaiswadi, 2017)
128	(Rasyidi, 2017)
129	(Rattanavayakorn and Premchaiswadi, 2015)
130	(Reijers et al., 2007)
131	(Saelim et al., 2016)
132	(Sakchaikun et al., 2018)
133	(Schönig et al., 2016a)
134	(Schönig et al., 2018)
135	(Sitova and Pecerska, 2020)
136	(Slaninová et al., 2015)
137	(Sophia and Sarno, 2018a)
138	(Sophia and Sarno, 2018b)
139	(Sophia and Sarno, 2019)
140	(Suriadi et al., 2017)
141	(Swennen et al., 2016)
142	(Wang et al., 2017)
143	(Y. Liu et al., 2012)
144	(Yahya, 2014)
145	(Ye et al., 2018)

146	(Zhao et al., 2020)
147	(Zhou et al., 2020)
#	**Resource role identification**
148	(Bozkaya et al., 2009)
149	(De Weerdt et al., 2015)
150	(Dustdar and Hoffmann, 2007)
151	(Hidayat et al., 2016)
152	(Jafari et al., 2020)
153	(Jin et al., 2007)
154	(Krutanard et al., 2015)
155	(Leitner et al., 2013)
156	(Porouhan and Premchaiswadi, 2015)
157	(Reungrungsee et al., 2012)
158	(Yang et al., 2018)
159	(Zhao and Zhao, 2014)
#	**Social network identification**
160	(Agostinelli et al., 2020)
161	(Ahn and Kim, 2020)
162	(Aloini et al., 2020)
163	(Alvarez et al., 2018)
164	(Appice et al., 2016)
165	(Appice, 2018)
166	(Boulmakoul and Besri, 2013)
167	(Caron et al., 2014)
168	(Dustdar and Hoffmann, 2007)
169	(Ferreira and Alves, 2012)
170	(Gao et al., 2009)
171	(Ghazanfari et al., 2010)
172	(Gupta et al., 2014)
173	(Hanachi et al., 2012)
174	(He et al., 2019)
175	(Hidayat et al., 2016)
176	(Jafari et al., 2020)
177	(Kamal et al., 2017)
178	(Kouhestani and Nik-Bakht, 2020)
179	(Krutanard et al., 2015)
180	(M. Park et al., 2016)
181	(M'hand et al., 2021)
182	(Pan and Zhang, 2021)
183	(Pinto et al., 2015)
184	(Porouhan and Premchaiswadi, 2015)
185	(Premchaiswadi and Porouhan, 2015)
186	(Prokofyeva et al., 2020)
187	(Raitubu et al., 2019)
188	(Rattanavayakorn and Premchaiswadi, 2015)
189	(Reungrungsee et al., 2012)
190	(Sakchaikun et al., 2018)
191	(Sellami et al., 2012)
192	(Slaninová et al., 2015)
193	(Soboleva and Tushkanova, 2020)
194	(Song and van der Aalst, 2008)
195	(Sun et al., 2020)
196	(van der Aalst and Song, 2004)
197	(Wang et al., 2016)
198	(Wongvigran and Premchaiswadi, 2015)
199	(Yahya, 2014)
200	(Zhao and Zhao, 2014)
201	(Zhao et al., 2019)
#	**Work organization mining**
202	(Ahn and Kim, 2020)
203	(Appice, 2018)
204	(Delgado and Calegari, 2020)
205	(Estrada-Torres et al., 2021)
206	(J. Park et al., 2016)
207	(Martin et al., 2017)
208	(Martin et al., 2021)
209	(Ogunbiyi et al., 2021)
210	(Porouhan and Premchaiswadi, 2015)
211	(Song and van der Aalst, 2008)
212	(Tang and Matzner, 2020)
213	(Thomas et al., 2017)
214	(Zeng et al., 2013)
215	(Zhao and Zhao, 2014)

8.6. Overview of Statistical Classification of Economic Activities in the European Community

Table 18. NACE sector list as taken from Statistical Classification of Economic Activities in the European Community, Rev. 2, 2008.

Sector
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A - Agriculture, Forestry And Fishing
B - Mining And Quarrying
C - Manufacturing
D - Electricity, Gas, Steam And Air Conditioning Supply
E - Water Supply; Sewerage, Waste Management And Remediation Activities
F - Construction
G - Wholesale And Retail Trade; Repair Of Motor Vehicles And Motorcycles
H - Transportation And Storage
I - Accommodation And Food Service Activities
J - Information And Communication
K - Financial And Insurance Activities
L - Real Estate Activities
M - Professional, Scientific And Technical Activities
N - Administrative And Support Service Activities
O - Public Administration And Defence; Compulsory Social Security
P - Education
Q - Human Health And Social Work Activities
R - Arts, Entertainment And Recreation
S - Other Service Activities
T - Activities Of Households As Employers; Undifferentiated Goods- And Services-Producing Activities Of Households For Own Use
U - Activities Of Extraterritorial Organisations And Bodies