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SCHOOL OF ECONOMICS AND BUSINESS

MASTER THESIS

PROCESS MINING IN THE GERMAN PUBLIC SECTOR

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AUTHORSHIP STATEMENT

The undersigned Sobiah Abdullah, a student at the University of Ljubljana, School of Economics and Business, (hereafter: SEB LU), author of this written final work of studies with the title Process Mining in the German public sector, prepared under supervision of Mojca Indihar Štemberger and co-supervision of Frank Morelli.

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LIST OF ABBREVIATIONS

AI – Artificial Intelligence

BI – Business Intelligence

BMWK – (ger. Bundesministerium für Wirtschaft und Klimaschutz); Federal Ministry of Economics and Climate Protection

BPM – Business Process Management

BPMN – Business Process Model Notation

BPR – Business Process Reengineering

CAZ – Corona Abstrich Zentrum

CMMI – Capability Maturity Model Integration

COE – Center of Excellence

CRM – Customer Relationship Management

DEMIS – (ger. Deutsches Elektronisches Melde- & Informationssystem für den Infektionsschutz); German Electronic Reporting and Information System for Infection Protection

DREAMY – Digital Readiness Assessment Maturity

ERP – Enterprise Resource Planning

ETL – Extraction, Transformation, Load

GDPR – General Data Protection Regulation

ID – Case Identifier

IEEE – Institute of Electrical and Electronics Engineers

IfSG – (ger. Infektionsschutzgesetz); Infection Protection Act

MES – Manufacturing Execution System

RKI – Robert Koch Institute

RPA – Robotic Process Automation

SCM – Supply Chain Management

SORMAS – Surveillance, Outbreak Response Management and Analysis System

UML – Unified Modelling Language

1 INTRODUCTION

Every process has potential for improvement. The identification of weak points and the introduction of corresponding improvement measures represent a major challenge. Possible solutions are not always clear-cut and are associated with uncertainties. Client requirements and business models are changing faster than ever. Even with sophisticated planning, organizations are not sure whether the desired effect will emerge. Every organization must therefore continuously review and improve its own processes. The innovative technology of process mining can help here.

The starting point for process mining research was in 1999 at the University of Eindhoven by Van der Aalst. After little event data was available in the beginning, this research area has been pushed forward in the last ten to fifteen years as significantly more data became available. Thus, software tools, algorithms, and methods for process mining emerged around 2005. Meanwhile, process mining algorithms have been implemented in many academic and commercial systems. In addition, there is an active group of researchers working on process mining. The use of commercial process mining software has been going on for more than about ten years. In 2012, only a small number of studies attested to the applicability of process mining, according to De Weerdt et al. (2013) in the meantime, many case studies on process mining have been published, which will not be discussed in detail here. This is not done here, because the present work focuses on the potentials of process mining for public administration.

The public sector's operations have been criticized for being sluggish and inadequate, resulting in resident frustration (Maleyeff & Campus, 2007). Since citizens' desires and aspirations are not satisfied, they become disappointed. Organizations typically follow such procedures to provide services that meet the needs of their clients. These processes are designed to convert administrative inputs into specific outputs that satisfy customers (Bergman & Klefsjö, 2010). As a result, municipal agencies must constantly assess and upgrade their processes to meet the needs and demands of their customers. People are not willing to tolerate any service the government offers, so there is a sense of urgency and significance in the public sector for process improvements (Ha & Lee, 2010).

Process mining has the potential to revolutionize the processes within any institution (Salzmann, 2019). Any deviations from the target process can be easily identified and tracked visually and with the support of key performance indicators. Hidden, previously unknown bottlenecks, inadequacies and resulting costs as well as the potential for further automation can be discovered. Process mining is based on different data sources that systematically generate so-called process instances (cases) based on events and can be dynamically tracked by human users in the form of dashboards (Celonis SE, 2021). In combination with key figures and conformance checks with the target process, precise analyses are possible. Furthermore, process mining enables to find the relevant facts and to understand them better in detail. Process mining software can help institutions to visualize information from the transaction systems of an authority and provide more detailed information to discover optimization potential in the process (Van der Aalst, 2012).

The public sector in Germany is undergoing drastic changes: digitalization, structural changes in the labour market and demographic change are influencing all areas of public administration. With its Digital Agenda, the German government is creating the framework for the future: The declared goal is a citizen-friendly, digital Germany with binding standards for nationwide digitization (BMWK, 2021).

There is an almost infinite number of processes in a public institution. They are often found wherever an application is made and then some kind of approval process rolls through the instances. These processes can be small and manageable or extremely complex, with many participants and decision variants (Lück-Schneider, 2016).

In the case of these more complex processes, the question often arises as to how they run in reality:

- Are there deviations in the actual behaviour of the process from the originally planned sequence?
- Are there idle times that can be avoided?
- Does the process behave according to the rules?

It is predictable that as e-government progresses, process mining techniques will also become highly relevant for public administration. This method has enormous potential, especially for fully automated processes. Poorly designed user interfaces that lead to incorrect submissions or information, could be quickly detected. Initial difficulties, which are likely to be in retrieving suitable data, should disappear as the method becomes more popular. Likewise, actual staffing bottlenecks can be quickly uncovered (Lück-Schneider, 2016).

The purpose of this research is to contribute to understanding the applicability of process mining in the public sector and to find out which prerequisites need to be fulfilled for a successful implementation. Furthermore, a major reason for this study is to help the institution by improving their processes. Consequently, getting a better understanding of how other public institutions like public health department or municipality could be optimized in order to minimize the chances of similar failures going forward. After all, the costs and resources that are being put into such projects, represent a significant amount and could have a dramatic effect on the process performance. This thesis will therefore go deeper into the underlaying errors in order to learn from prior mistakes, while also looking into the key success factors.

The goals are:

- To prepare an overview of requirements for process mining in the public sector.
- To contribute to the findings of how to increase efficiency in German government.
- To identify the readiness and the attitude of the public administration towards process mining.
- To determine discrepancies from the intended process handling.
- To analyse a process in a selected institution and to propose improvements.

Primary and secondary data will be both included in the thesis to achieve the goal of this work. The secondary data will be illustrated by a literature review based on present data, primarily research outcomes in academic journals, literature and official databases.

In order to gain a thorough understanding of the subject, this paper will also depend on primary data. The primary data was gathered by learning about a concrete public institution’s process. In this case, the data collection form of choice was expert interviews, where the data was gathered mainly through interviews with key personnel involved in the paper's selected processes. The interviews were conducted in a semi-structured manner to increase the understanding of the different tasks and functions that are involved in the process. Furthermore, this thesis also includes a use case scenario for the application of process mining in public administration. The conception of a use case in cooperation with a public institution serves the operationalization of this project. The outcomes of the primary data collection were evaluated and compared to existing literature, with a concentration on success factors regarding process mining implementation. Recommendations were made based on the findings.

Details such as the institutions name, ethnicity and other revealing information were altered due to confidentiality obligations on the part of the institution under inquiry. To retain anonymity, pseudonyms were also used.

After the introduction in the first chapter, the second chapter is composed of the theoretical foundations. This is intended to give theoretical foundations, a basic understanding of the overarching subject area, and the technology under consideration. In addition to fundamental concepts, the current state of research is also presented. The third chapter describes the applied research methods used to collect data. Subsequently, the results from the previous chapter are presented and explained in chapter four. Before the conclusion, the fifth chapter discusses the results and gives possible suggestions for improvement.

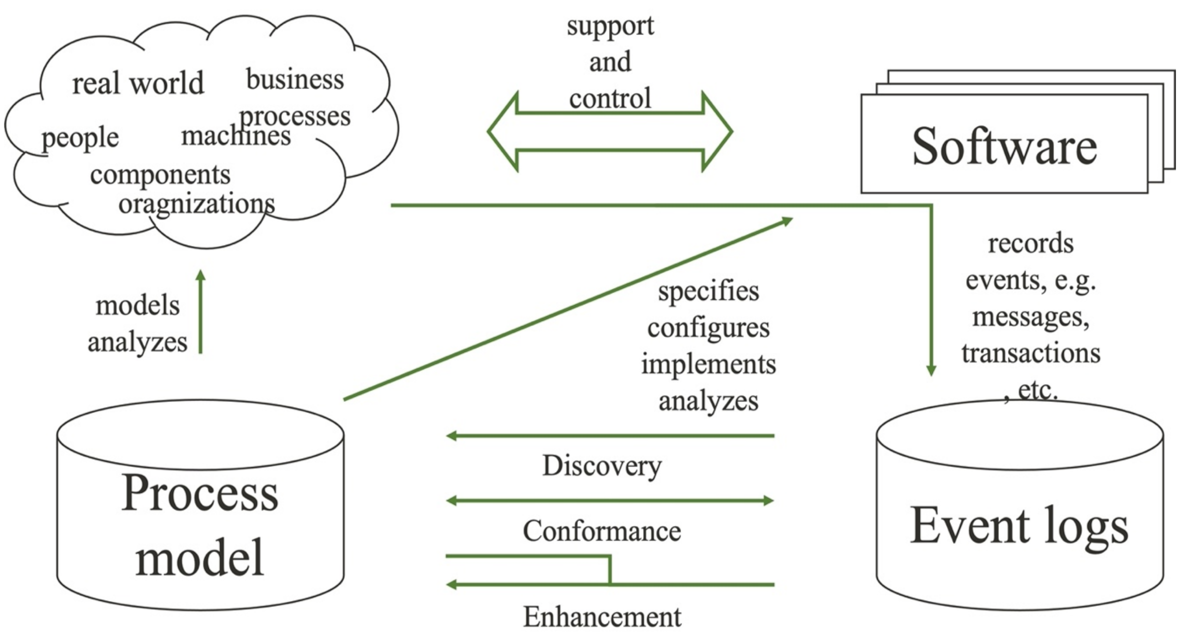
2 THEORETICAL FUNDAMENTS

The topic of process mining has become omnipresent in the field of Process Management. Likewise, there is a multitude of publications dedicated to the topic. The following chapter begins with a definition, classification and delimitation of process mining, in particular to the terms business intelligence (BI), data mining and business process management (BPM). Subsequently, the functionality is considered, whereby it is subdivided into the process, the data origin and the event log. This is followed by a look at the quality assurance of the data basis and then by an introduction to the types of process mining. Furthermore, the guiding principles and the current state of research are elaborated. And finally, the opportunities and challenges are discussed.

2.1 Development of process mining

The emergence of process mining took place from the two areas of BI and process modelling. "The general idea of process mining is to take, as input, some event data (e.g., event log files) and perform a fact-based analysis of process executions." as explained by Burratin (2015). This supplements with the interpretation of Van der Aalst (2010, p. 90 & 2011, p. 172), who also understands the idea of process mining as the recognition of real business processes based on event logs from information systems, which can also be monitored and improved through this and is shown in Figure 1.

Figure 1: Positioning of the contents in process mining



Source: own work based on Van der Aalst et al. (2022).

Buck-Emden (2018) explains process mining as follows: "process mining is a generic term for procedures for analysing business processes based on digital traces (log or protocol data) that business process instances leave in the system during their execution." Fitting to this is Munoz-Gama's (2017) understanding that "process mining techniques use unbiased information contained in event data to support the management of process models." In summary, the author follows the understanding that through process mining, companies use and analyse data from BPM systems to understand how their business processes work.

To gain a better understanding of process mining, it is important to classify and delineate the term in relation to BI, data mining, and BPM.

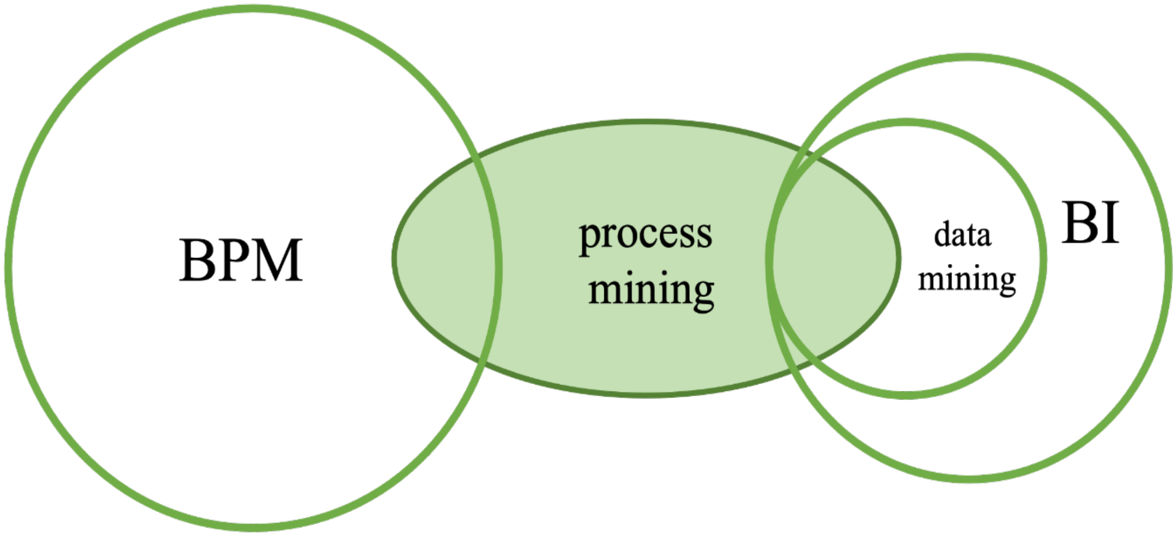
BI comprises technologies and methods for the acquisition of information with the aim of supporting strategic and operative decisions (Van der Aalst, 2011, p. 192). For this purpose, data of the company, the markets, the customers and the competitors are evaluated (Peters & Nauroth, 2019, p. 21). BI tools enable the analysis of very large data sets and are often very user-friendly. The analyses and evaluations are used for reporting and are often visualized with dashboards. For this purpose, various tools and techniques of data mining are used, but the focus of these is not on the process view, but on the data and decision making (Burratin, 2015, p. 23). There are similarities between BI and process mining in the extraction, preparation and loading of data, which means that the same tools can be used. However, process mining exceeds the possibilities of classical BI-tools concerning process analysis (De Weerdt et al., 2013, p. 57).

As mentioned above, data mining methods are used for process mining. Through procedures and algorithms, data mining enables the automated analysis of large amounts of data. The data stock is examined for knowledge, patterns and relations in the data sets. With the help of the findings from data mining, decision makers can be supported. Analogous to BI, data mining and process mining also differ in terms of orientation since process mining is process-oriented and therefore requires different algorithms (Schönig, 2015, p. 26).

BPM aims to improve processes (originally business processes). It attempts to achieve this objective by formulating methods for eliciting, describing, representing and executing as well as configuring, monitoring and analysing business processes (Leno et al., 2018, p. 6).

The tools and techniques of BPM use process models. An increasing use of BPM systems success for operational process support. The process models are used to configure such systems as well as to analyse the actual and target state. In most cases, however, these models are not linked to actual event data, which makes the analysed results unreliable, since they are not based on observable facts but on ideal models. At this point, process mining complements existing approaches to BPM (Van der Aalst et al., 2012, p. 3).

Figure 2: Disciplines related to process mining



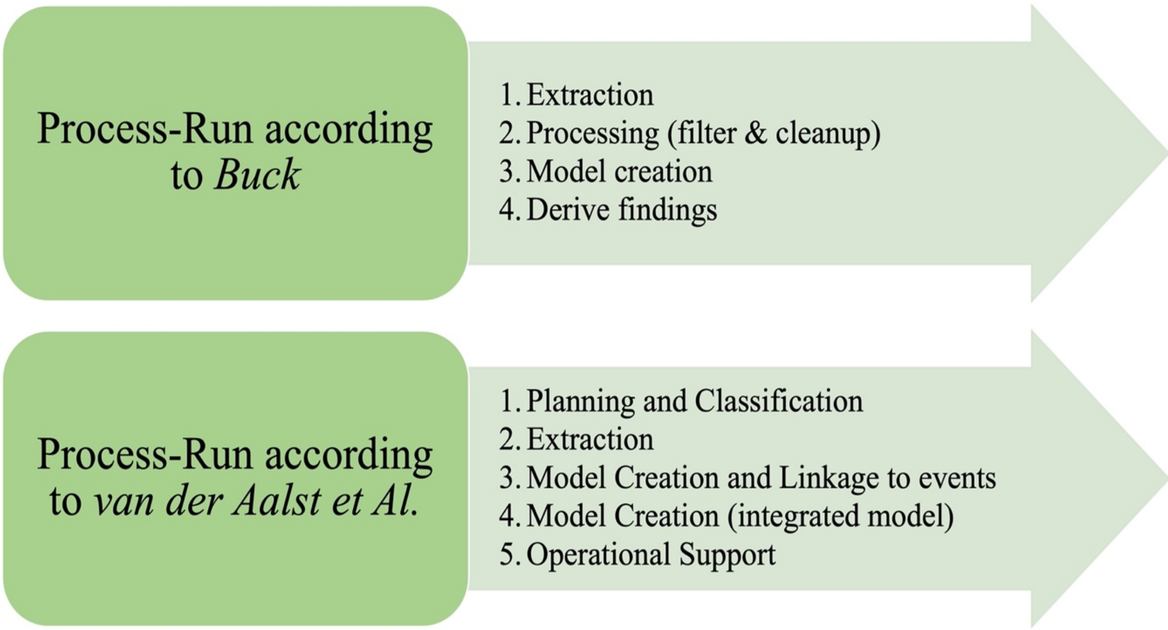
Source: own work.

In summary, the goal of process mining is to bridge the gap between BI, especially data mining, and BPM, as shown in Figure 2. In addition, the combination of process models and event data enables a new form of process-oriented analysis. Yet, a categorization of process mining, due to the broad spectrum, is not clearly possible. Furthermore, the objectives of process mining overlap with other approaches (Van der Aalst, 2016, p. 44).

Before going into the topic of process mining in more depth, it is first necessary to clarify what a process is. In process mining, a process is a chain of events consisting of process steps with a unique start- and end-activity. These process steps are individual actions or events in the process. The process starts with a starting point and ends with an end point. These points and all intermediate steps are process steps (Buck-Emden, 2018, p. 2; Van der Aalst et al. 2012, p. 177).

The approach of process mining can be divided into different phases, two possible processes according to Buck-Emden (2018) and Van der Aalst (2012) are shown in the following Figure 3. Based on the two processes, it can be seen that the process steps can differ, but the basic procedure remains the same.

Figure 3: Procedure of process mining



Source: own work based on Buck-Emden (2018, p. 2); Van der Aalst et al. (2012, p. 177).

The data to be analysed can come from a large body of formats, including text files, PDF documents, excel files, transaction logs, or database tables (Van der Aalst, 2016, p. 125). These formats often originate from information systems, as this is where the traces of the activities performed are usually stored (Burratin, 2015, p. 23). In addition, the data for a single process can also be merged from multiple systems. Similarly, a process can be analysed across organizations, thereby incorporating cross-organizational sources (Peters & Nauroth, 2019, p. 10). Often, the data to be analysed does not come from a single database, creating an effort to extract actionable log data. For this purpose, the data can be made available in a data warehouse or data lake, for example, and then extracted and collected separately.

In the case of cross-site or cross-company data sources, it is necessary to have the ability to extract the data. In these cases, there is another requirement for usability: the presence of transaction references and attributes (Van der Aalst, 2016, p. 126).

The following list of possible sources is intended to illustrate the variety of data sources from which data can be extracted for process mining (Schönig, 2015, p. 30):

– Customer relationship management (CRM) systems
– Databases (historical data, e.g. in an .xls file)
– Web pages
– E-Commerce web protocol

- Enterprise Resource Planning (ERP) systems
- Manufacturing Execution Systems (MES)
- Social media platforms
- Supply chain management (SCM) systems
- Workflow systems
- BPM systems

This list is not complete and shows only a part of the possible data sources. In addition, manual or non-IT processes can also be considered as part of process mining, but this data must be manually prepared and imported into the event log. Examples include e-mails or mail archives, PDF documents and scanned text documents. Since this manual preparation is usually time-consuming and uneconomical, data from such sources is rarely used (Peters & Nauroth, 2019, p. 10).

The procedure for extracting the data follows the ETL process (Extraction, Transformation, Load). First, the data is extracted from the external data sources (extraction), then the data is transformed into the desired format (transformation), and finally the data is loaded into the target system (loading). This target system can be a database or a data warehouse. The result of the ETL process is the event log (Van der Aalst, 2016, p. 127).

2.1.1 Event logs

For a better understanding of process mining, it is essential to know and understand the specific terminology. The technical terms used in process mining are explained below.

- Event: An event describes an atomic activity with the minimum requirements case identifier (ID), activity and timestamp, and represents the smallest data unit in process mining. The case ID is the unique activity number for a case. This can be an order number, customer number, purchase order number or a personnel number (Van der Aalst, 2011, p. 77). An activity represents a concretely executed process activity or a process step. For example, „Create Purchase Requisition“ or „Create Purchase Order Line Item“ (Peters & Nauroth, 2019, p. 9). A timestamp contains date and time when an activity was started or/and finished. At least one timestamp is required (Peters & Nauroth, 2019, p. 9).

- Case: It consists of several events and represents a process flow. All process steps within a case always have the same case ID.

- Trace: A trace is a series of events within a control flow relation. The chronological execution sequence of the events of a process instance is taken into account.

– Event Log: Several process-related traces are combined in one log. Event logs form the basis for the application of process mining.

Each case consists of a sequence of events that are executed within a process instance. A unique sequence of events from the beginning to the end of a process instance is called a process variant, and each case/track belongs to exactly one variant (Suriadi et al. 2017, p. 2). In addition to the minimum requirement attributes of case ID, activity and timestamp, additional optional attributes are often stored in data tables (Van der Aalst, 2016, p. 128).

Figure 4: Event log

Attribute

Instance

Events

Case ID	Activity	Start time stamp	End time stamp	Resource	Role
1	Create Purchase Requisition	2011/01/01 00:00:00.000	2011/01/01 00:37:00.000	Kim Passa	Requester
1	Create Request for Quotation Requester	2011/01/01 05:37:00.000	2011/01/01 05:45:00.000	Kim Passa	Requester
1	Analyze Request for Quotation	2011/01/01 06:41:00.000	2011/01/01 06:55:00.000	Karel de Groot	Purchasing Agent
1	Send Request for Quotation to Supplier	2011/01/01 11:43:00.000	2011/01/01 12:09:00.000	Karel de Groot	Purchasing Agent
1	Create Quotation comparison Map	2011/01/01 12:32:00.000	2011/01/01 16:03:00.000	Magdalena Predutta	Purchasing Agent
1	Analyze Quotation comparison Map	2011/01/01 22:44:00.000	2011/01/01 23:13:00.000	Immanuel Karagianni	Requester
1	Choose best option	2011/01/01 23:13:00.000	2011/01/01 23:13:00.000	Tesca Lobes	Requester
1	Settle conditions with supplier	2011/01/02 01:22:00.000	2011/01/02 09:20:00.000	Francois de Perrier	Purchasing Agent
1	Create Purchase Order	2011/01/02 09:58:00.000	2011/01/02 10:10:00.000	Karel de Groot	Purchasing Agent
1	Confirm Purchase Order	2011/01/02 14:09:00.000	2011/01/02 14:43:00.000	Sean Manney	Supplier
1	Deliver Goods Services	2011/01/02 20:49:00.000	2011/01/03 03:37:00.000	Sean Manney	Supplier
1	Release Purchase Order	2011/01/03 11:20:00.000	2011/01/03 11:21:00.000	Elvira Lores	Requester
1	Apporve Purchase Order for payment	2011/01/03 19:09:00.000	2011/01/03 19:10:00.000	Karel de Groot	Purchasing Agent
1	Send invoice	2011/01/04 00:54:00.000	2011/01/04 00:54:00.000	Kiu Kann	Supplier
1	Release Supplier´s Invoice	2011/01/04 15:08:00.000	2011/01/04 15:13:00.000	Karalda Nimwada	Financial Manager
1	Authorize Supplier´s Invoice Payment	2011/01/04 15:13:00.000	2011/01/04 15:13:00.000	Karalda Nimwada	Financial Manager
1	Pay invoice	2011/01/04 15:22:00.000	2011/01/04 15:31:00.000	Pedro Alvares	Financial Manager
2	Create Purchase Requisition	2011/01/01 00:16:00.000	2011/01/01 00:29:00.000	Immanuel Karagianni	Requester
2	Create Request for Quotation Requester	2011/01/01 08:00:00.000	2011/01/01 08:26:00.000	Alberto Duport	Requester

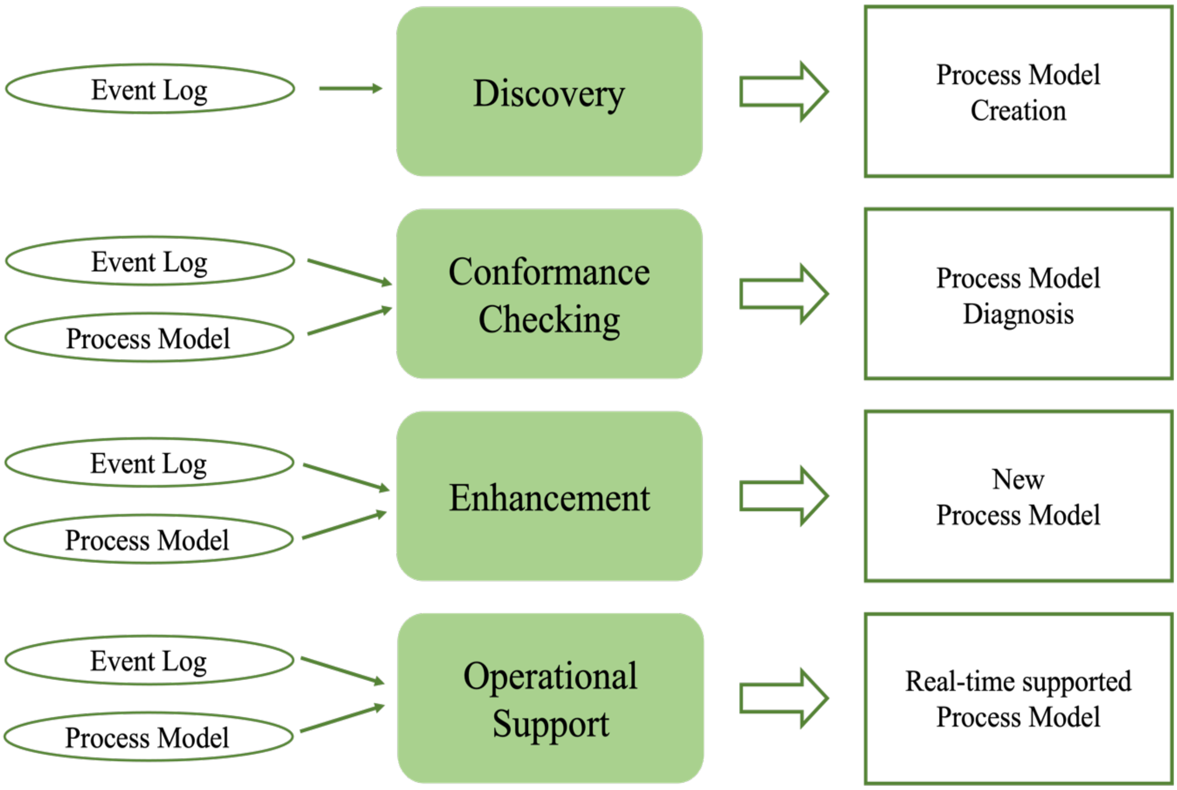
Source: own work.

These can be enriched to the event logs and thus allow more extensive filtering and analysis. Depending on the use case, resources, roles, costs, start- and end-time, stamps are useful and necessary for some process mining algorithms. Resources, for example, are details about a person who performed an activity. A role describes the position of a person within a network. Personnel dependencies within a process is analysed with this information. Costs and start- and end-time stamps allow a more detailed efficiency analysis, for example, analyses of storage costs per storage location, bottlenecks, throughput times and waiting times. These qualitatively enhances process mining projects and offer more viewing options. In the course of this, the performance must always be considered, which is demonstrably more burdened the more attributes and filtering are used. However, this problem has been significantly mitigated with today's more advanced and robust algorithms. In Figure 4 an example of an event log is shown. The extraction of data from an event log is an essential part of process mining activities. The event log must contain the relevant data for the process under consideration. Based on the traces of the underlying IT systems (i.e., database entries), process mining algorithms can reconstruct actual process flows by associating events with activities. In this context, a trace represents a sequence of events within a control flow relationship in the sense of a chronological execution order of the events of a process instance (Van der Aalst, 2016, p. 128).

2.1.2 Process Mining Types

In the literature, there are two different approaches regarding the characteristics of process mining. On the one hand, three types are differentiated: discovery, conformance checking, enhancement. This approach is followed by the large body of the literature. On the other hand, Peters and Nauroth (2019) have extended this existing characterization by a fourth type, the operational support of IT-based systems. Van der Aalst (2011) also mention this fourth type. In the following, all four types are shown in Figure 5 and explained afterwards (Van der Aalst, 2016, p. 244).

Figure 5: Process mining types

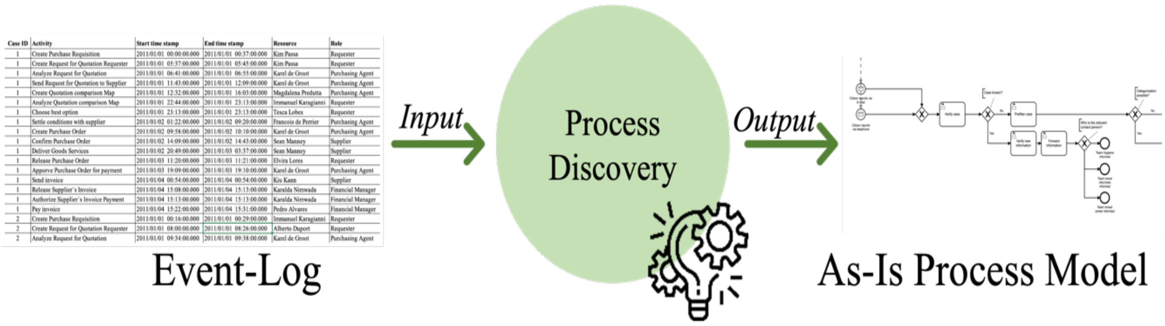


Source: own work based on Morelli & Noe (2021).

2.1.2.1 *Discovery*

The first process mining type is discovery of models. Discovery techniques are used to automatically generate actual process models from event data (Van der Aalst, 2016, p. 244). *Figure 6* illustrates the procedure of an universal discovery process.

Figure 6: Discovery procedure



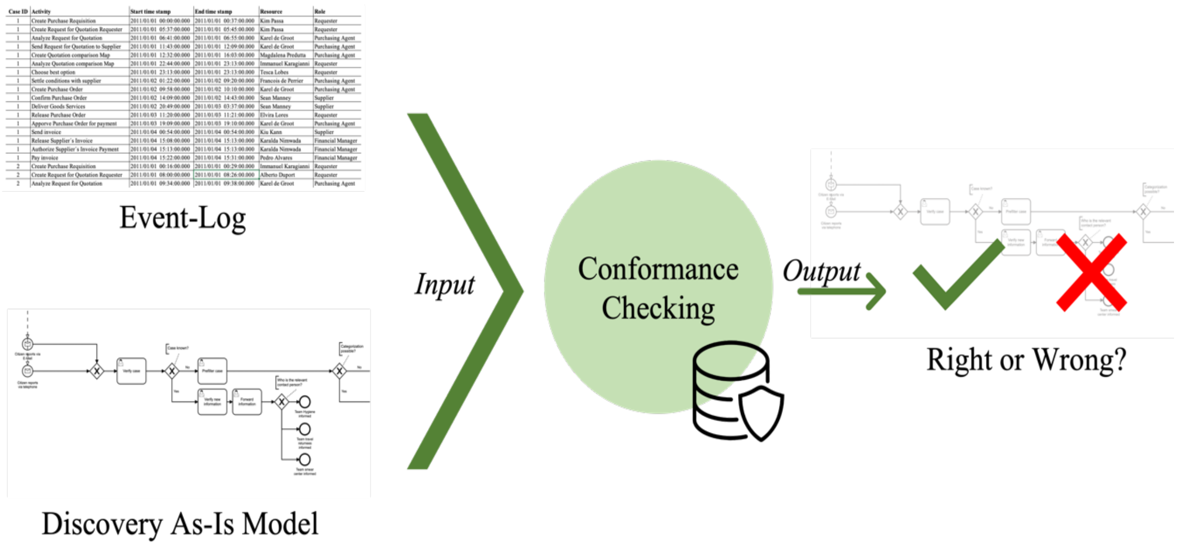
Source: own work based on Van der Aalst (2011).

For the discovery, the stored events are used, which refer to specific process instances, such as payment in a sales process for a specific customer number. Additional information is not required for deriving the models from the event logs. Often, the resulting models are described as process models (e.g., Business Process Model and Notation [BPMN] model) (Burratin, 2015, p. 14). BPMN 2.0 is a recognized standard for modeling business processes with a comprehensive set of symbols for business process diagrams and is considered the counterpart to the Unified Modeling Language (UML) used in software development. (Lindenbach & Göpfert, 2012) Most process mining methods are applied for this expression and well-known methods are the Alpha-Algorithm, the Heuristics Miner or the genetic process mining. For the representation of the process model, as mentioned before, different possibilities exist. Flowcharts and logical rules can be mentioned as examples (Van der Aalst, 2011, p. 77).

2.1.2.2 *Conformance Checking*

The second type of process mining is conformance checking. For this, the event log of the process is compared with an existing process model or the process instructions. This means that the actual process models resulting from the first expression are compared with existing process models (Peters & Nauroth, 2019, p. 6).

Figure 7: Conformance Checking procedure



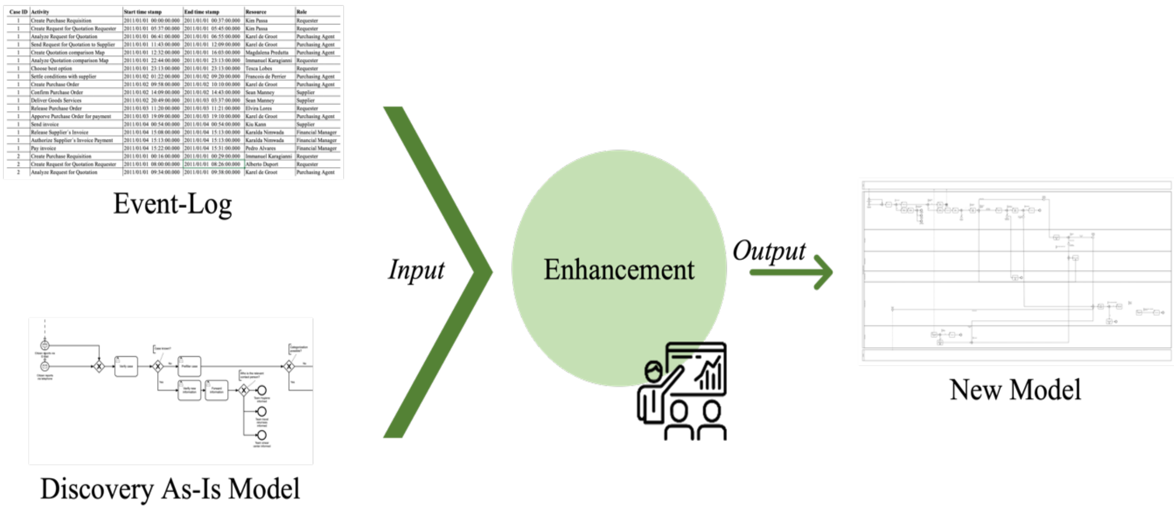
Source: own work based on Van der Aalst (2011).

A BPMN model, for example, serves as a reference model, as in this present work. Likewise, the check is based on organizational charts, declarative models, business rules or guidelines. In addition, the actual observed processes from the event logs are compared with models that were identified as actual process models at an earlier point in time using process mining. The objective is to verify that the logged process executions match the existing process model and vice versa. There are two possible perspectives on the discrepancies: One is that the model is wrong and does not represent reality. On the other hand, the event log is wrong and the reality deviates from the desired model (Munoz-Gama, 2017, p. 4). Furthermore, this process mining type can be used to verify whether a process documentation is still up to date, or the model still represents reality. The techniques for conformance testing thus provide metrics on the degree of conformance and allow explanations of observed deviations. Furthermore, it is possible to analyse the observed deviations in more detail and to determine the extent as well as to assess the quality of the process models. The methods of conformance testing require event data and models as input (e.g., BPMN models), as it is shown in Figure 7**Fehler! Verweisquelle konnte nicht gefunden werden.**. Diagnostic data concerning the discrepancies between event log and model are the output (Van der Aalst, 2011, p. 77-79).

2.1.2.3 Enhancement

The third process mining type is enhancement. In this case, the existing process model is extended or improved based on the actual process executions, which is portrayed in Figure 8. The objective of this type is to change the existing process model. With the help of the previously determined deviations, not only the existing process model, but ultimately the underlying business process is improved or extended. With this characteristic two possibilities can result: The error removal and the model extension (Schönig, 2015, p. 28). In the case of error correction, the existing process model is adapted in order to bring it closer to reality, to the actual processes. For model extension, on the other hand, additional perspectives are added to the process models. Possible perspectives are performance, time and resources. An example of this is the enhancement of the event log to include time stamps. As a result of this enhancement, bottlenecks and lead times can be identified and optimized. This results in an extended or improved process model. Analogous to the compliance check, the enhancement also requires the event data as well as models as input and outputs an enhanced model (Van der Aalst, 2010, p. 90).

Figure 8: Enhancement procedure



Source: own work based on Van der Aalst (2011).

2.1.2.4 Operational Support

The fourth process mining type results in operational support of IT-based systems for processing. To achieve this, integration of process mining tools into operational systems as well as user interpretation is required. This type results from the possibility of increasingly using process mining techniques online. Using information from completed cases and cases in progress, insights are gained to generate recommendations or predictions. This type is also intended to support the correctness of the process being executed. An example for this, is the detection of a rule violation at the moment of occurrence. Furthermore, predictions on the remaining process time for an ongoing case is made based on historical information from similar cases. In addition, the event data of an online store is compared with historical data to detect deviations and derive countermeasures from them (Peters & Nauroth, 2019, p. 6).

2.1.3 Guiding principles

The Institute of Electrical and Electronics Engineers (IEEE) Task Force on process mining has adopted a process mining Manifesto that formulates six guiding principles. Peters and Nauroth (2019) also refer to these six guiding principles, which should be considered for the commercial, practically oriented use of process mining and are listed in detail below.

Guiding principal 1: Substantial events are carriers of important information.

Process mining is performed based on event logs, as described previously. The quality of event log has a major effect on the quality of the process mining results. Peters & Nauroth (2019, p. 7) have declared quality criteria to ensure that the quality of the data is suitable for process mining.

Criteria for event data quality are Resilience (integrity), Correctness, Completeness, Defined meaning (semantics), Data protection (personal data), Data security (misuse or loss) and Transparency (Peters & Nauroth, 2019, p. 7).

Table 1: Maturity levels

Maturity level	Characteristics	Example
R I	• Poor quality of event logs Events incorrectly or incompletely represent reality	Handwritten processing comments and notes
R II	• Events are the byproduct of an information system (automatic recording) • No systematic approach to recording • Information system can be bypassed • Event data incorrect, incomplete, inaccurate	Event data from production systems or work overviews
R III	• Automatic recording of events, but unsystematic • Resilient event log • Completeness to be checked	Database tables from ERP systems
R IV	• Recording is automatic, systematic and reliable • Completeness and resilience given • Use of process instances and activities	Event data from BPM or workflow systems
R V	• Event recording as in maturity level 4, in addition defined event logs • Quality is excellent • Data protection and data security are considered • Clear semantics for recorded events	Semantically enriched event data from BPM systems

Source: own work based on Van der Aalst et al. (2011, p. 180).

A breakdown into maturity levels is used to describe the quality. For the resilience of the results from process mining, the quality and the integrity of the data used is crucial, since lost or untrustworthy event data will lead to less valuable results. Likewise, the usability and automated creation of process models depend on the quality and integrity. The maturity level is used to measure and ensure the quality of the data. According to the process mining Manifesto of the IEEE Task Force on process mining, five maturity levels are differentiated. The individual maturity levels are described in Table 1 below.

It is possible to apply process mining to data with maturity levels R1 and R2, but the analysis is problematic and may not produce reliable results, which is why data with maturity level R3 is mostly used. Due to the automatic recording from maturity level R3 onwards, there is a high probability that reality is mapped.

Guiding principle 2: Specific questions for event log data extraction.

When using process mining technologies, a company should always pursue specific goals, such as identifying process optimization potential or diagnosing process deviations.

For the deployed process mining methods to deliver the desired output, the company should be guided by certain questions. First of all, the company must be clear about which process is going to be examined with the help of process mining methods. On the one hand, a clear delineation between different processes creates clarity and, on the other hand, enables the company to target a specific process. Once the process to be investigated is known, the question arises as to which data should be analysed (Van der Aalst et al., 2011, p. 180).

In addition to the maturity of the event log, the level of detail of the event log data and its attributes have an influence on this question. It is purposeful to match the quantity and quality of the data to one's own requirements. For example, if you are looking at a purchasing process, it makes sense to be able to trace the document flow for individual order items. Attributes such as the identification number of the order items, the order number or the material number are required for this purpose (Peters & Nauroth, 2019, p. 8).

Guiding principle 3: Fundamental control flow concepts are supported (concurrency, options, etc.).

Process representation differs depending on the process mining tool. Often, well-known modelling options such as BPMN, UML or Petri Nets are used. Process mining should be able to represent the basic order relations of a process, such as parallels (logical AND-connections), decisions (XOR-) or loops, regardless of the representation form. However, complex process operations such as the identification and interpretation of concurrency in the event log are not recognized by all process mining technology. Knowing the coarse process structure, it therefore makes sense to choose process mining software that covers the control flow features known to the process (Van der Aalst et al., 2011, p. 181).

Guiding principle 4: Events should be related to model elements.

The process model created by the software for process mining is based solely on event log data. During matching and enhancement of process mining, the event log data is compared with the data of a reference process model and visualized. The prerequisite for this is that the used software can correctly interpret the relationships between the reference model and the actual model, in order to be able to display them realistically. The event log must therefore be created in such a way that the database is sufficient for this comparison (Peters & Nauroth, 2019, p. 8).

Guiding principle 5: process mining model as a goal-oriented abstraction of reality.

Models derived from event data provide views of reality. In this context, such a view should represent a goal-directed abstraction of the behaviour captured in the event log. With respect to an event log, there are multiple views that are useful. Furthermore, different stakeholders require different views. For example, models determined from event logs should be viewed as maps (e.g., geographic maps). Making a visual distinction between relevant and unimportant information is useful. It is helpful, for example, to display frequently occurring activities in the process visualization in a larger size than activities that occur infrequently. Furthermore, contents can be distinguished from each other by colour (Van der Aalst et al., 2012, p. 183).

Guiding principle 6: process mining is a continuous process.

Recognizing that the process models generated show the process flow over a period of time, organizations should not view the use of process mining tools as a one-time project. By contrast, processes adapt rapidly to changing environmental conditions, so a static process model may become obsolete at a later point in time. Process mining itself should therefore be treated like a process and carried out systematically at continuous time intervals. The power of modern database management systems is sufficient to enable process mining in near real-time. Process mining tools are consequently no longer exclusively suitable for the analysis of historical data but they are also gaining in importance regarding operational process management (Peters & Nauroth, 2019, p. 9).

2.1.4 Opportunities and Challenges

2.1.4.1 Opportunities

The previous chapters already give an impression of the potential behind process mining. Organizations can benefit from a fast and simple process visualization in different ways. Modern process mining tools can, for example, display information about time and resource requirements or the control and data flow in the process model (Van der Aalst et al., 2011, p. 183).

There is also the possibility to show process deviations or to identify bottlenecks and to mark them in a meaningful way. As a result, those responsible for the process gain deep insights into the actual process flow. These insights can then be used as a basis for working on the processes (Gadatsch, 2020, p. 163; Peters & Nauroth, 2019, p. 31). Process management is to structure, analyse and document processes in order to bring them in line with corporate goals with the help of communication and information systems (Gadatsch, 2020, p. 1). In process mining, it is possible to deal with the constantly growing amount of process data and to combine it in a process model in a meaningful way (Prostean et al., 2020, p. 310). The process models generated by process mining can then be used to predict process flows. This provides process owners the opportunity to anticipate and respond to potential difficulties in the process flow. It is also possible to check whether the current process execution matches the optimal process execution (Greasley, 2019, p. 308). Of particular interest is the possibility to control the process flow using real-time information provided by the process mining software (Peters & Nauroth, 2019, p. 23). In addition, process mining offers the possibility to ensure compliance with internal and external rules and regulations by reporting rule violations or preventing them through intelligent predictions (Peters & Nauroth, 2019, p. 23).

In conclusion, the potential of process mining for the optimization of processes is reviewed. In principle, process optimization makes a significant contribution to maintaining and increasing the competitiveness of a company. Basically, this is done by aligning the central process flows with the requirements of the customers. Accordingly, the decisive point for process optimization is the understanding of customers and processes (Gadatsch, 2020, p. 36).

A more detailed look at this classification shows the potential of process mining. Information extracted from actual process execution with the help of a process mining tool, supports the user in understanding the process under consideration. The key is a realistic representation of the process flow. Simultaneously, the automated identification of process flows saves time and resources. Process mining software can generate the process model independently without manual intervention, so new users can learn about the process with little time and without much prior knowledge (Li et al., 2015, p. 1195).

In addition, to further increase the optimization potential of process mining, process mining methods can be combined with other technologies. An example of this was the collaboration between the process mining software manufacturer Celonis and the Robotic Process Automation (RPA) provider UiPath. These two companies have cooperated with each other to identify processes with high automation potential and process them automatically with the help of a software robot (Van der Aalst et al., 2018, p. 3).

If process mining is used sensibly, it has the potential to make a company's entire process landscape more efficient. Both, the identification of individual process flows as well as process management and process optimization, benefit from it. Nevertheless, process mining methods should not be seen as a panacea for all of a company's process-related problems. It is always useful to compare the potential demonstrated with the limitations of this technology.

2.1.4.2 Challenges

Van der Aalst (2012) has mentioned eleven challenges that occur before, during and after the implementation process of process mining.

Challenge 1: Finding, merging, and cleaning event data.

To extract event data suitable for process mining, several hurdles must be overcome. It is important to note that the data may be spread across many sources. Therefore, they must first be merged. In addition, the data may be incomplete. While it is possible to derive the missing data, this requires a lot of effort. Also, there may be outliers in the event logs. In order to clean the data from these, it is first necessary to define what exactly outliers are and how they can be detected. Last but not least, it should be noted that event logs have different levels of granularity and occur in a specific context.

Challenge 2: Dealing with complex event logs with different characteristics.

Event logs can have a large body of characteristics. For example, event logs that contain a very large amount of information can be difficult to handle. Event logs with too little information, on the other hand, may not be critical to reliable results. It is important for companies to find out whether an event log is suitable for process mining or not. For this purpose, the trial-and-error method is recommended.

Challenge 3: Create representative benchmarks.

Benchmark analysis is very important for improving process mining components, such as tools or algorithms. The analysis should consist of sample sets and relevant quality criteria. The benchmark data should be based on real datasets on the one hand and synthetic datasets on the other hand. Synthetic datasets can help improve process mining techniques needed to deal with data that is, for example, incomplete or noisy.

Challenge 4: Dealing with concept drift.

Concept drift is a situation in which processes change while they are simultaneously being analysed. The occurrence of concept drift can be detected by dividing the event logs into smaller event logs and analysing them individually. It is important to understand concept drift well so that the management of processes is error-free.

Challenge 5: Improve the representation bias used for process discovery.

The selection of a representation bias for process discovery should be carefully and thoroughly considered. It is important that the target language was deliberately chosen during representation bias, and not just the aspect of representation as the main factor in the selection, to ensure high quality results.

Challenge 6: Balancing quality criteria such as suitability, simplicity, precision, and generalization.

There are four quality criteria that compete with each other: Suitability, simplicity, precision, and generalization. In a model with good suitability, all traces of an event log are perfectly reproduced. A good simplicity model explains the behaviour of an event log in an understandable way. Precision models ensure that the behaviour of an event log is not beyond the scope of the log. Finally, a model should generalize behaviour, not constrain it. The challenge here is to find a model that balances the criteria.

Challenge 7: Cross-organizational Mining

Typically, process mining is used only within an organization. However, modern technologies such as service technologies or cloud computing lead to scenarios, where event logs from different organizations are used for analysis. There are two types of collaboration. In the first case, collaboration is done by splitting the analysis process and distributing it among the organizations. The individual results are then combined. In the second case, the collaborating organizations each perform the process themselves and share their experiences with each other.

Challenge 8: Providing operational support.

Compared to the past, where process mining was mainly used for historical data, today data is updated in near real-time. Moreover, events are analysed as soon as they occur if sufficient computing power is available. Therefore, process mining is also used for online operations support analysis, not just offline analysis. There are three operations support activities: detect, predict, and recommend.

Challenge 9: Combining process mining with other types of analytics.

The challenge is to combine analytics technologies from operations management and data mining, such as simulation and visual analysis, with process mining to gain more insights from event data.

Challenge 10: Improve usability for non-experts.

The goal of process mining is to create living process models, for example models that are used daily rather than archived. That is, users can interact with the results of process mining daily. Consequently, the challenge is to hide the advanced process mining algorithms behind user-friendly interfaces. In this way, appropriate parameters and suitable analysis methods can be automatically set and suggested.

Challenge 11: Improving comprehensibility for non-experts.

It often happens that process mining results are not understandable enough for users. This can lead to wrong assumptions. Therefore, it is necessary to choose meaningful representations to illustrate the results. It should also be made clear how trustworthy the results are.

2.2 Process mining in the public sector

The lack of literature on this subject leads to the fact that only the basic points are shown. This field is relatively unexplored, because of the lack of contact with process mining.

Nevertheless, the public sector is in the throes of digitization: Structural change in the labour market and demographic change are influencing all areas of public administration and public institutions. The German government is laying the groundwork for the future with its Digital Agenda. The stated objective is a digital Germany that is friendly to its citizens and has mandatory requirements for national digitalization. Transparency, efficiency and customer orientation are to be the hallmarks of the future sector (Zahorsky, 2018).

Process mining can help precisely achieve these goals with a combination of real-time evaluation of processes, automated recommendations for action to improve processes, and intuitive usability. Streamlining internal processes in government agencies and institutions of all kinds is urgently needed because undesirable loops, bottlenecks and inefficiencies in these processes increase complexity and cause administrative and personnel costs to skyrocket. This is compounded by a lack of transparency and knowledge about their own processes (Manfreda et al., 2015, p. 471).

3 METHODOLOGY

This section outlines the methodology that is important for later analysis. The methodology consists of three parts. First, the object under study is introduced, with the aim of giving a clear illustration and understanding of the subject in a form of a case study. In the second subchapter, the primary data collection method expert interviews, is explained and applied. The interview guide is attached in the appendix. This method describes the best free and natural situation. In this way, results can be deeply interpreted and inquired with the subjects. The last subchapter shows a prototypical approach using Celonis.

3.1 Case study research

For the methodology, case study research for qualitative data collection is applied and a use case is examined to operationalize the question of the applicability of process mining in administration. For this purpose, requirements from the user's perspective are going to be operationalized and a generalizable state is to be identified.

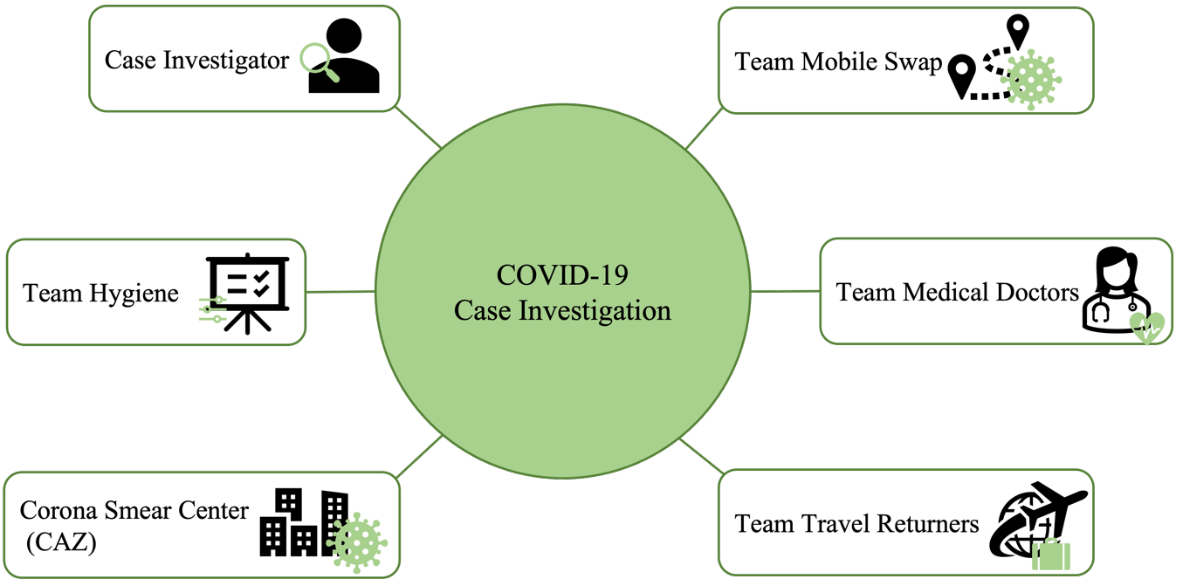
As a research tool, case studies aim to provide an adequate representation of reality. Case studies are based on empirical investigations that analyze a current state in a practical context. Holistic, empirical, interpretive, and empathic can be named as the main framework for this method (Gemmel, 2014, p. 8). In the absence of a clear boundary between observation and context, the use of case study research has proved to be more appropriate. Therefore, the general conditions of the phenomenon to be observed must also be taken into account. Related studies therefore analyze relationships and processes using different methods and data sources (Thomas, 2021, p. 11). According to Yin (2018), the incorporation of a sharply defined theoretical foundation is notably essential to ensure generalizability of the results.

To locate and map processes in the administration that are suitable for process mining, an approximate draft of inventory analysis of the project sponsoring authority is carried out in this study. The object of the study is a district office in Germany, which is anonymized for data protection reasons. The process selected on the basis of the inventory analysis describes the case investigation of citizens infected with COVID-19. The district office under consideration provided presentations, results from workshops and graphics as preliminary information for this purpose. The process is mapped using the business process modeling language BPMN 2.0.

The initial aim of the case investigation process is to record data of ill citizens in the pandemic respectively to collect and manage COVID-19 data. Different teams are used during this process (see Figure 9):

- Case Management: Associated staff members of the administration section take over a case, process it and either hand it over to another team or close it.
- Mobile Swab Team: The team is available to citizens who cannot leave their homes for health or similar reasons. For this purpose, there is a zoning in subdistricts.
- Hygiene Team: This group makes sure that all rules and regulations are followed and takes care of quarantine compliance, for example.
- Doctors Team: Corresponding persons treat symptoms that occur, perform tests and issue certificates in case of illness.
- Corona Smear Center (CAZ): In this testing center, smear tests are performed upon prior registration and presentation of an official identity document.
- Travel Returners Team: The team checks whether citizens have traveled from a risk area and must therefore comply with certain quarantine periods, for example.

Figure 9: Involved parties in Case Investigation



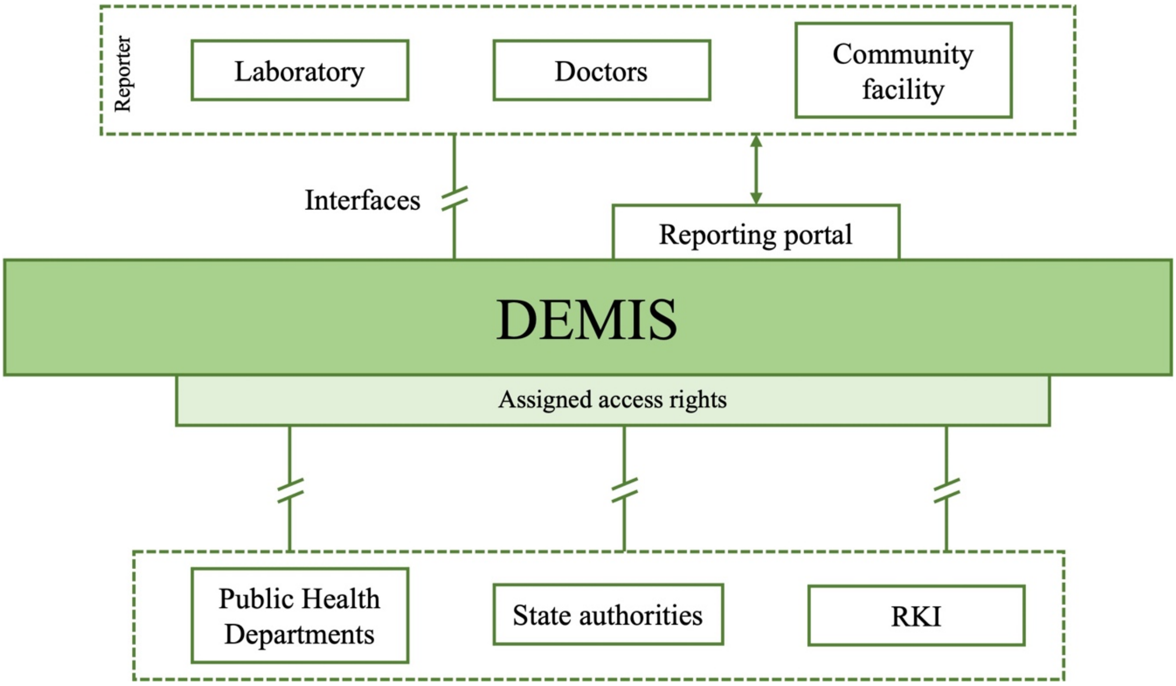
Source: own work.

Besides the involved humanly work, following IT-systems were attached:

– <u>MS Access Database</u>
  For general use and administration, the district office works with an MS Access database. This database is used for all case processing. Input data is transferred from SurvNet and output data is also entered there. The database is used to document and track content such as personal information, infections, contacts, disease status, and history.

– <u>DEMIS</u>
  It stands for "Deutsches Elektronisches Melde- und Informationssystem für den Infektionsschutz" which means "German Electronic Reporting and Information System for Infection Protection". It is the reporting software used to forward COVID-19 test results to the public health department and district office. DEMIS will further develop and improve the existing reporting system for infectious diseases in accordance with the German Infection Protection Act (i.e., Infektionsschutzgesetz [IfSG]). In particular, starting with the reporting parties (medical doctors, laboratories and others), a continuous electronic information processing will be made possible. This is intended to reduce the workload for the reporting parties and the responsible authorities. Moreover, information on emerging infectious diseases can be made available more quickly in the future to those responsible in the health offices, the responsible state authorities and at the Robert Koch-Institute (RKI). Furthermore, the cooperation of the parties involved and the exchange of data between them will be better supported, so that even large infection events can be processed more effectively. Figure 10 displays an overview (RKI, 2021).

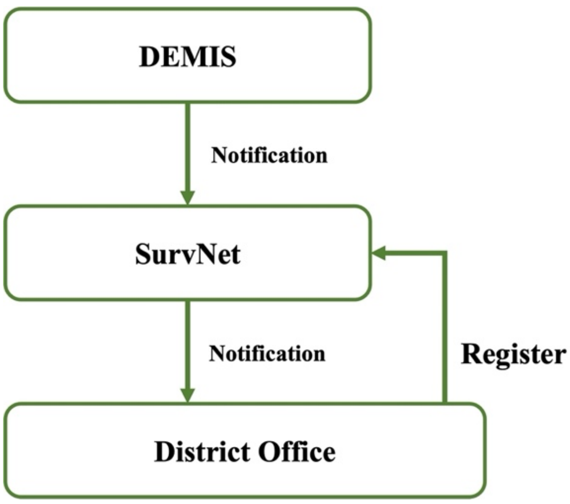
Figure 10: DEMIS



Source: own work based on RKI (2021).

– <u>SurvNet</u>
  The RKI provides the SurvNet@RKI software free of charge to health departments and district offices, which is used to collect, evaluate and forward reporting data in accordance with the Infection Protection Act. In principle, SurvNet files are created from DEMIS reports (i.e. the report of a test), which in most cases correspond to positive cases (RKI, 2021). Figure 11 illustrates the relation of SurvNet to DEMIS and the district office.

Figure 11: Positioning of SurvNet



Source: own work.

After receiving a message by email or telephone from an entity, the system checks whether a case has already been created. If this is the case, new information is added and forwarded to the respective team. If not, any categories are checked to create a case. If no case is created, the entity is advised and feedback is given.

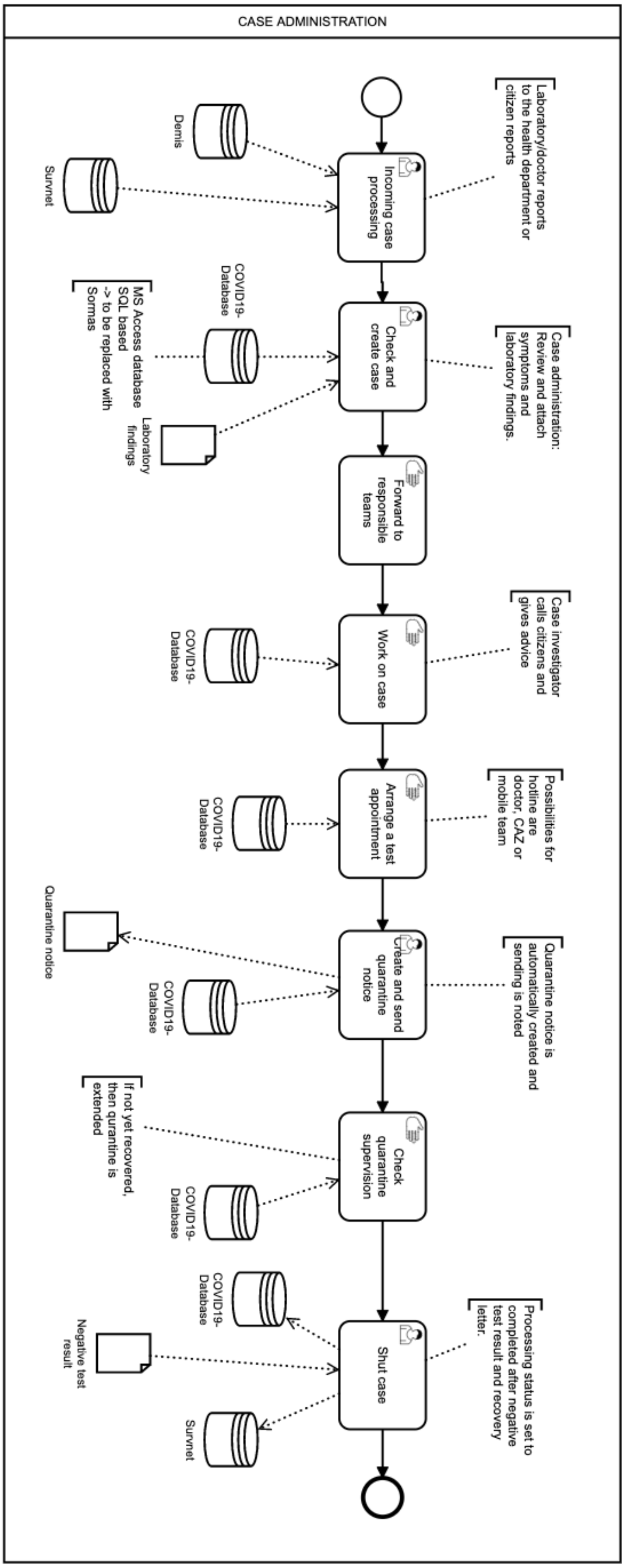
If the case can be categorized, the case is taken up and symptoms are asked for. In the lack of symptoms, the presence of laboratory findings must be checked.

If the findings are positive, the hygiene team is called in, which then follows up with a hygiene-related check. This is a sub-process, in which it is decided whether and where a swab must be taken. The choice is between a mobile smear team or CAZ. With the mobile smear team, the smear is taken and then repeatedly transferred to the process step check findings. If the smear is taken at the CAZ, the prerequisites for the smear must be checked. If the prerequisites are complied, the smear test can be performed, if not, public testing centres or the relevant authorities are contacted. If no other options are available, the case must go through verification again.

In the case of negative or absent laboratory findings, it must be checked whether it is a travel return. If this is the case, it will be forwarded to the return team. Otherwise, the potential relevance for a smear test must be checked. If the smear is not desired, the case will be closed. However, if a smear is desired, the CAZ will be contacted.

If symptoms are present, doctors are notified. Two attempts are made to contact the target person. If the target person is not reached on both occasions, the case is closed. If the contact is successful, measures are determined, either a swab is taken and then forwarded, or a medical consultation is performed. As a third measure, a quarantine can also be imposed. After the quarantine period is determined, it is pronounced, and a quarantine notice is sent. The latter may result from several teams. The process is summed up in Figure 12.

Figure 12: Summary of Case Investigation process



Source: own work.

3.2 Expert Interviews

In research, collecting primary data is the usual procedure to answer questions that are specific to any topic. Based on the research question and goal, three basic types of primary data collection are available: Observation, Experiment, Survey (interviews and questionnaire). Primary data are collected by the researcher conducting the research (Saunders et al., 2019).

The expert interview is a survey method which, when used in a scientific context, is one of the qualitative methods of social research. In its simplest form, this method aims at expert knowledge. This form of knowledge is tied to its carriers, the experts (Saunders et al., 2019).

The advantage of the method is the free and natural situation of the interviews. You can interpret results in depth with the respondent and ask follow-up questions. You also control the interview situation and ensure that the respondent is not stressed, for example, and statements are therefore to be interpreted differently. You also offer a high information content through the detailed answers of the respondents.

Nevertheless, the following points must be limited (Saunders et al., 2019):

- Social undesirability: Subjects can prettify their answers by the presence of the researcher.
- Sampling: You only interview a small group and are therefore not very representative.
- Subjectivity: The evaluation of the answers is subjective and can be interpreted in many ways.

For the purpose of the methodological classification of qualitative expert interviews, it is necessary to critically reflect on two central aspects in particular: The question of who is considered as an expert at all, and the question of what type of knowledge is generated through expert interviews. First, the concept of the expert, from the perspective of the sociology of knowledge, the expert is differentiated from the non-expert on the one hand and from the expert on the other. The first distinction seems immediately obvious. While the non-expert has general or everyday knowledge, the expert has a specialized knowledge that can be understood as socially institutionalized expertise (Sprondel & Grathoff, 1979, p. 141). Hence, expert knowledge is tied to a function or professional role (Robert, 2014, p. 41). A guided, open-ended interview is the standard and recommended data collection instrument for expert interviews. To conduct expert interviews, different variants are available (Kaiser, 2014, p. 38):

- Explorative expert interviews serve either to gather general information in a previously little-researched subject area (with the aim of forming hypotheses), to prepare a systematic main investigation (also by generating technical know-how for the researcher) or to open up the field in the sense of identifying relevant experts.

– Guideline-based expert interviews are more structured forms of questioning with the aim of obtaining hard facts that cannot be ascertained from other sources, or only to a limited extent. By means of the interview guide, the survey is conducted with the clear goal of retrieving specific knowledge necessary to answer an already precise, and theoretically embedded research question.

– Plausibilization interviews can be useful after the empirical research program on its results has been completed, either to arrive at practical recommendations for action or to get hints on how to present the research results.

For successful data collection through the semi-structured interview, it is necessary to prepare the data collection, and thus the interviews and the interview guide.

For the preparation of a semi-structured interview, Saunders et al. (2019) recommend considering the five Ps: Prior, planning, prevents, poor and performance. In addition, three measures to avoid data quality problems are mentioned: Knowledge level of the researcher, timely development of topics and provision of information to the interviewee, and an appropriate interview location.

The interview guide serves two functions and is an important component of research preparation. First, the guide assists in analyzing the issues in the process. Second, the guide supports data collection. Consequently, the interview guide plays an important role in the entire research process. The configuration of the interview guide varies from broad topics to detailed questions.

Considering the measures described by Saunders et al. (2019), a literature review is the basis of the interview guide. In addition, the literature review enhances the researcher's knowledge and assists in identifying topics for the interview. The interview guide for the underlying research begins with introductory questions and then becomes more specific. This introduces the interviewee to the topic before asking specific questions about the process and process optimization in terms of process mining. In addition, the guide supports the comparison of theory and practice. The interview guide for the research can be found in Appendix 2.

An appropriate sample has a significant impact on the research results. It is not possible to examine the entire population of institutions that offer or use process mining as part of the empirical study. Therefore, the results are based on a sample on the chosen experts.

Vignali et al. (2011) characterize samples in qualitative research as small, non-random, and theoretical. Since the choice of an appropriate sample differs depending on the survey method, questions arise as to how to select the companies specifically or how to gain access to the companies, according to the qualitative methodology. Interviewees are selected through personal contacts and recommendations. This approach is followed because it is hardly possible to determine who understands the process.

The targeted selection of experts is based on their ability to provide information about the respective research area. The experts must meet certain criteria. For example, the experts must have in-depth experience and knowledge of a clearly defined task, which enables them to structure a topic in a meaningful way for others. In addition, experts are considered a medium for generating knowledge, because they are able to testify to the topic under study. The status of expert is given to the specific question of inquiry in a certain way by the researcher. Experts are not always found at the top level of an organization. Tendentially, the second and third levels of a hierarchy have more detailed knowledge of internal structures, procedures, tasks, and events.

Four semi-structured interviews have been conducted as part of the study. For this purpose, an interview guideline was developed before the start of data collection, covering relevant topics related to the process. This served as a guide for the interviews, which were conducted in an open manner. This meant that the order of the questions was changed or the questions were asked differently. This was decided at short notice based on the course of the respective interview. For evaluation purposes, the interviews were recorded and transcribed in consultation with the experts.

The conception of the guide contains three segments: By asking for general information such as field of activity and tasks, a targeted mutual understanding for the following questions is to be created. In this way, the specific questions in the subsequent interview can be targeted to the content of the interviewee's area of expertise. The interviewees should then first express their general opinion of the process and then report on their specific experiences with the process.

The selected experts come from different fields: Interviewee 1 works in consulting and deals with topics of organizational and process analysis. The second interviewee is a city secretary in the administration of the pandemic staff of the district office. This person is also involved with the Department of Sanitation and Health. Interviewee 3 functions firstly as a public health professional and secondly as the head of the pandemic staff. His range of tasks consists, for example, of coordinating staffs, developing sufficient situation descriptions and perspectives for the future. The fourth interviewee works in senior services and characterizes his work as a containment scout. The term containment scout was introduced by the RKI in April 2020 and describes tasks such as fast and effective contact tracing as their job. Thus, its scope includes case management of citizens with COVID-19 disease and contact tracing.

The following query collected respondents' impressions of the overall process. In the classical sense, such feedback forms the basis for a process evaluation and optimization measures based on it. For the present case study, this should enable a comparison with the analysis results based on a process mining model.

The final part deals with specific experiences of the interview partners with the process of case investigation. The following issues are discussed in this context:

- Collaboration with third parties, for example database specialists, schools, hospitals, other district offices, and employers.
- Use of IT systems such as MS Office, also systems such as SurvNet and SORMAS (Surveillance, Outbreak Response Management and Analysis System).
- Weaknesses in individual process steps such as information deficits, media changes, duplicate work and the resulting additional workload.
- Bottlenecks that occur and their causes.

Finally, potential for improvement in case finding is identified, for example through better IT support, avoidance of duplication of work, skill improvements among employees and an increase in the degree of standardization.

3.3 Prototype process mining Deployment

The creation and evaluation of prototypes is one of the constructive-qualitative methods of business informatics. The objective is to generate a quickly available, executable preliminary version of an application system in order to present a proof-of-concept (Wilde & Hess 2006, p. 6).

In the context of this thesis, a prototype for case study processing has been developed. The associated primary objective is to gain generalized knowledge for the process mining approach in administration from the evaluation of the prototype. For this purpose, the process mining tool from Celonis was connected to an MS Access database and an exemplary data set provided by the district office.

From the incomplete data set provided by the cooperation partner an event log was created, synthetically enriched and from this a process mining model was automatically generated by the software tool of Celonis. It contains 1426 activities and 479 cases that started on 5 different days. Compared to the amount of data that is generated in reality, this is only a small sample. For the mapping of consistent process variants, the data set was harmonized.

Through the analysis with the help of the tool, aspects or correlations become transparent in the context of the process mining discovery that did not emerge from the expert interviews. For example, this includes the finding that processing a case as soon as it is assigned to a processor a second time takes an average of 3.5 days longer than in the regular case with a single execution.

Another fact that can be pointed out is that cases with a long processing time often involve a physician. This is illustrated in Figure 3, which visualizes the overall process in the prototype using two filters: First, there is a restriction to case processes with a longer duration (>72 hours) and second, externally performed swabs (by mobile teams) are excluded. The application of the filters proves to be a relevant approach to reach this conclusion.

However, it should be noted that due to the small amount of data, it cannot be assumed that the sample is representative.

4 PRESENTATION OF RESULTS

In this chapter all the findings conducted from the case study and the expert interviews. In addition, findings from the execution in Celonis will be shown just for illustration purposes.

4.1 Evaluation of the Case Investigation of COVID-19

All respondents criticized the effort required for duplicate entries in the DEMIS and SurvNet systems. However, since these systems operate separately and communication between them is not supported, the same data is stored separately on both systems. This not only results in duplicate entries, but also puts a lot of time into the process. Furthermore, the lack of digitization in the offices was criticized. For example, documents are sent by fax and documents are still kept on paper instead of being stored digitally. Furthermore, there is a lack of work equipment such as cameras, headsets, and so forth. In addition, the equipment of the workplaces is critically reflected. There is not enough space for team meetings and possibilities such as home office, especially during the pandemic, are not sufficiently supported. In addition, communication within and outside the teams appears suboptimal, so that different levels of information exist because new information is not passed on. One reason for this is that staff changes frequently. In connection with this, it takes a lot of time to train new employees. Also, there are complaints that the areas of activity are not precisely defined or demarcated from one another. This means, for example, that the citizens' hotline often neglects its tasks or delegates them to others, even though this is within its remit.

In terms of IT support, the aim is automatic integration with the COVID-19 database and the SurvNet system. Furthermore, the topics of home office and co-working spaces or flexibility with regard to the workplace are addressed, among other things due to limited room capacities for large team meetings. Also, there is a desire to promote an exchange of information and experience with institutions at the state and local level in addition to the recommendations and guidelines of the RKI. Overall, despite the problems mentioned, there is a positive basic tenor among all interviewees: The conclusion drawn, is that the case management process has developed well over time, which is attributed to the constant adjustments.

All respondents emphasize the importance of greater digitization of the process. With regard to IT support, the focus is on automatic integration with the COVID-19 database and the SurvNet system. Furthermore, the topics of home office and co-working spaces or flexibility with regard to the workplace are addressed, among other things due to limited room capacities for large team meetings. Additionally, there is a desire to promote an exchange of information and experience with institutions at the state and local level in addition to the recommendations and guidelines of the RKI. Overall, despite the problems mentioned, there is a positive basic tenor among all interviewees: the conclusion drawn is that the case management process has developed well over time, which is attributed to the constant adjustments.

Another complaint is that there are not enough rooms or workstations in general. This makes it difficult to hold team meetings in large groups. This limits the teams' communication with each other and also with other teams. Communication in general is also often criticized during the interviews. Due to poor or even non-existent communication, information is missing, outdated, or lost. In addition, employees are changed far too often, which also has a bad impact on the quality of information. For example, information such as addresses, or telephone numbers is often lost in the course of the process. Supplementing this missing information, or researching it again takes a lot of time. Other problems that arise due to a lack of communication but also due to a lack of management are, for example, the management of a COVID-19 case by different employees. This arises because either there are different names within the family, or the members of a family have reported their case at different times. Through adequate communication and management, the care of a family could be created by one employee, which not only ensures a good structure, but can also better oversee or reduce the workload.

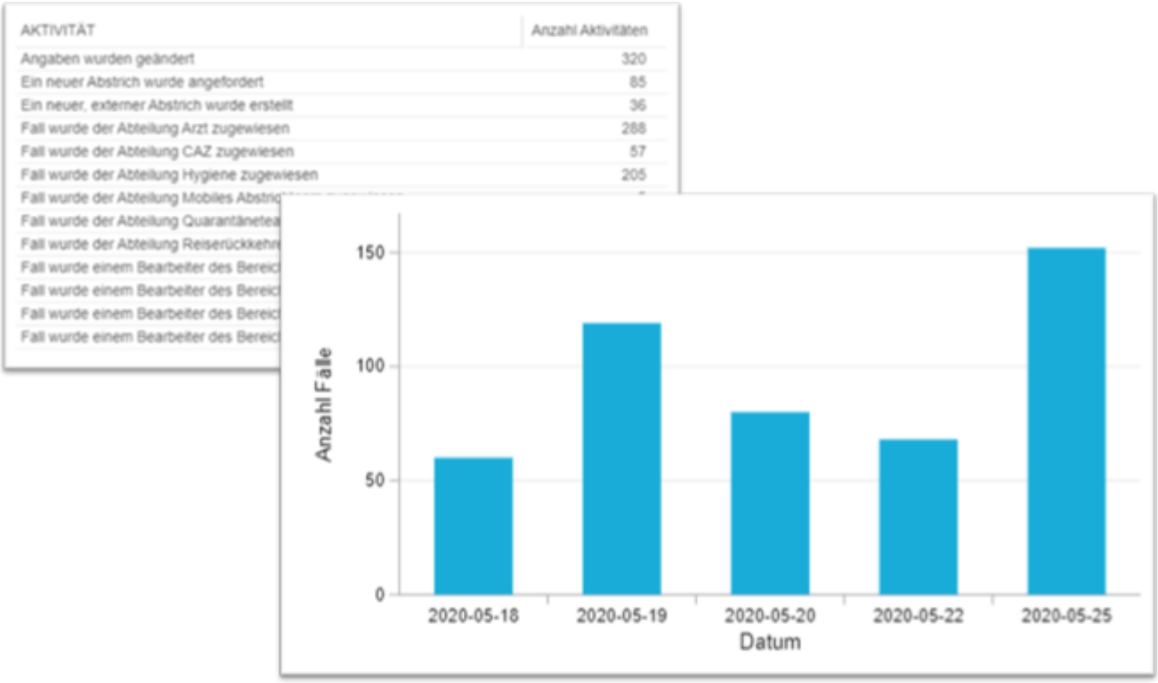
Despite many problems that are currently present in the process, the respondents nevertheless believe that the current process flow is in good condition. This has been achieved through constant adjustments and further development of the process. However, this does not mean that although the process is currently running well, it will continue to do so in the future. Above all, the aspect of digitalization could at some point ensure that the process no longer develops further.

4.2 Practical example of implementation with Celonis

The task is to enable a prototypical connection of the Access database to Celonis as a process mining technology. The aim is to develop a basic understanding of process mining and to clarify whether the use of Celonis process mining can add value to the public sector. A small excerpt of the data set was provided from the Access database for case administration. The data includes a history of activities in the application with time stamps. It should be noted that the present data set is not complete. The data used, only serves to illustrate the potential of process mining.

The limited data set as shown in Figure 13 contains 1426 activities and 479 cases that started on 5 different days.

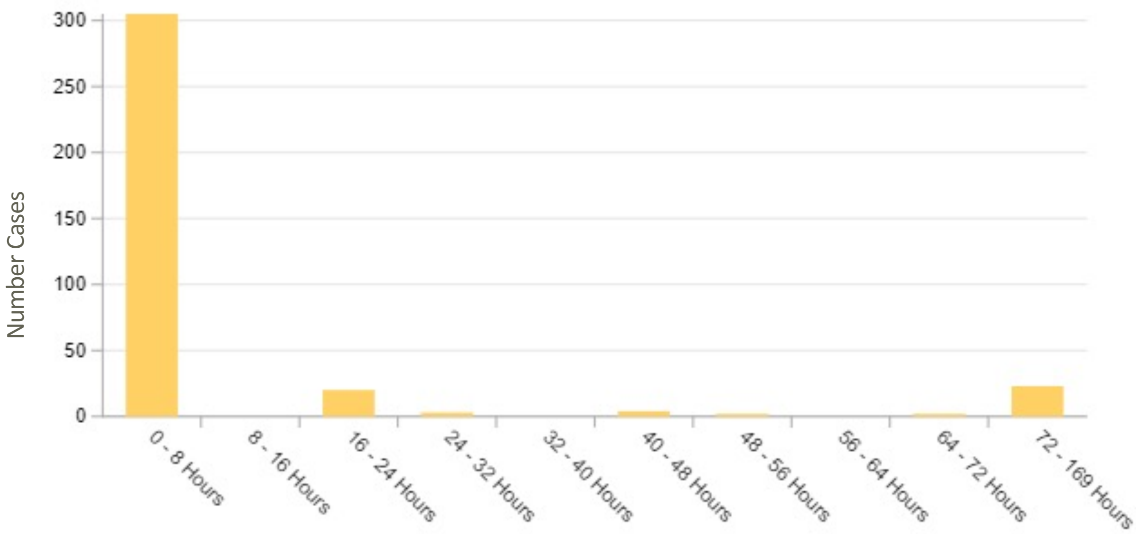
Figure 13: Representation of activities and case with Celonis



Source: own work.

Figure 14 shows that most cases are wrapped up within a time frame of no more than one day.

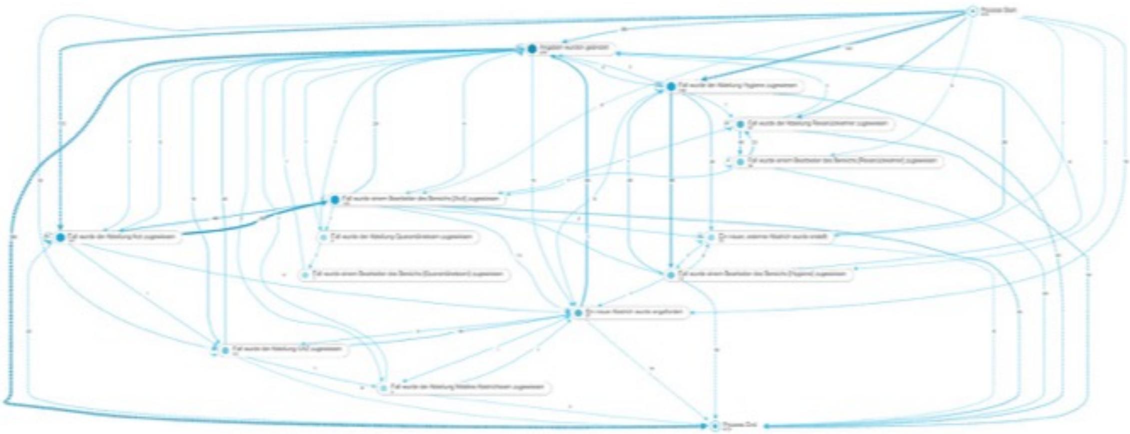
Figure 14: Number of cases closed with the duration with Celonis



Source: own work.

Figure 15 shows the entire process image. Due to the small amount of data, the process image with all the process variants is still manageable. The focus of figure 15 lies on the illustration of the process variants, which are the blue paths.

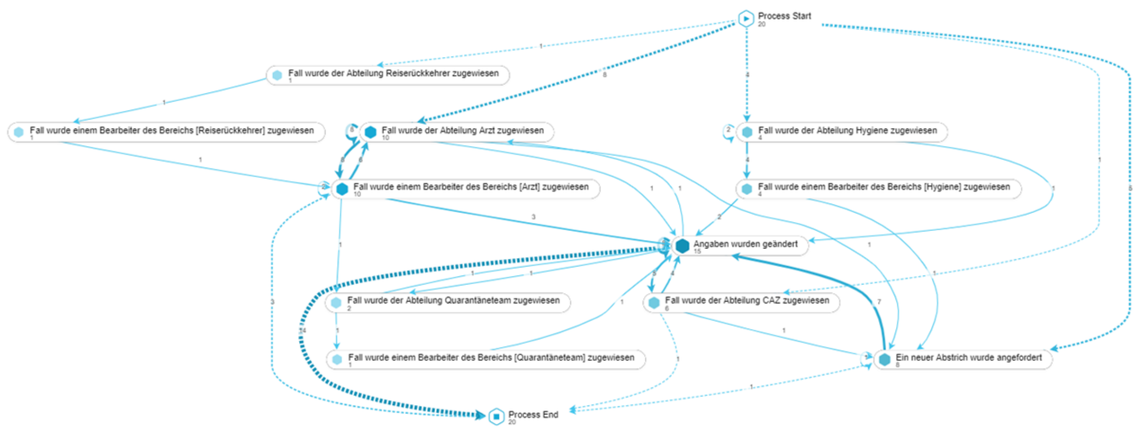
Figure 15: Entire process representation with Celonis



Source: own work.

For the purpose of illustration, aspects are shown that have important statements that would not be apparent without Celonis. The first selected aspect is that once the case is assigned to a processor, it took on average 3.5 days longer than in the normal case. Another aspect that can be shown is that cases with a long turnaround time (> 72h) often involve a medical doctor.

Figure 16: Entire process with filters with Celonis



Source: own work.

In Figure 16, the overall process is shown, applying a filter of less than 72 hours with regard to the lead time and a filter that excludes external smears. The aim of figure 16 is to illustrate, how applying filters can reduce possible process variants. The use of conformance checks in the generated model made it clear that the main variant could not be considered a "happy path". The target process for COVID-19 case finding had to be re-modeled, because the designated main variant did not meet all requirements. It has been created based on the interview results and agreed with the stakeholders. The target process was created using the modeling language BPMN 2.0 (see Appendix 2).

4.3 Perceived Challenges and Solutions

The COVID-19 case finding process had to be completely modeled from scratch due to a lack of information. The information provided was either not meaningful, or too limited to create a process. Therefore, with the help of graphics and personal information exchange, a basis for a custom process was created. The process was visualized using BPMN 2.0. Using this model is a crucial step for the representation of real processes and is therefore necessary for the implementation of process mining.

Furthermore, the available data for the event log was not provided in a consistent content context. Not all of the data was related to each other, so some of the data was unusable. In addition, no meaningful information could be derived from Celonis, because the amount of data entered was too small. However, as mentioned in Chapter 4.1, the results are only meant to be illustrative. The results only show the potential of process mining and how the technology can be used.

The interviewees were selected based on their area of activity to ensure that the results of the interviews actually describe the process. As described in Chapter 3, for open-ended and qualitative questions, the reason for the answer is recorded along with the answer to ensure that only objective and reasonable answers are recorded in the interview. Due to the fact, that the interviewees work in different fields, diverse results could be achieved. This led to a higher degree of interpreting. The interview was conducted without complications, meaning that there were no interruptions, and the established interview time frame was adhered too. The interviews were conducted uniformly on the basis of the previously established interview guide. At the same time, the uniform structure allows the preparation time for each interview to be shortened. A major shortcoming in conducting the interviews was the understanding of the questions. Because the questions were not properly understood, the respondents gave the same answer to several questions.

A prerequisite for successful implementation is a positive attitude and an active promotion of process mining by higher-level managers and decision-makers within public administration. They must establish a process culture that ensures sufficient acceptance. It must be communicated, for example also in communication with personnel councils, that process mining is not aimed at performance evaluation and control of individual employees, but at overall increases in effectiveness and efficiency.

It is up to the departments concerned to check whether the IT infrastructure in question is suitable with the application systems in use. If the existing information systems prove to be adequate, a suitable event log is generated. It is also determined whether process mining would be useful in day-to-day operations, in real time or close to real time by the users. Alternatively, a deployment within a process improvement project is possible.

Furthermore, the development of user groups proves to be of considerable importance: A large, area-wide spread seems generally desirable here in order to build up internal know-how in the public sector. A resulting community offers the possibility of creating even more extensive structures.

As a visionary, organizational solution for implementing the process mining approach in the public sector, the use of a Center of Excellence (CoE) solution seems suitable to ensure sufficient coordination in the future. This approach should also be seen as a vehicle for successfully scaling the digital transformation as a whole: The CoE is responsible for associated data security, quality, governance and compliance. Community knowledge is permanently communicated with the help of best-practice guidance and training and aligned with overarching goals. The CoE is also responsible for the administration of software licenses and the associated upgrade management. It also acts as an auditing and approval authority, ensuring compliance with relevant standards and defined practices (Ward-Dutton, 2020). Positive scaling effects or cost savings can be expected from this (Beuckes & Liesert, 2019).

The interaction of different CoEs in the decentralized structures of public administration poses a challenge. In this context, a stronger shift toward hybrid organizational forms appears desirable. The hybrid model is a mix of centralized and decentralized approaches, as is often found in corporate practice (Beuckes & Liesert, 2019). This can only be achieved in the medium and long term through a willingness for the federal, state and local governments to work together. Pilot projects, for example, could be set up in advance in order to use quick wins frequently used from corporate practice, to create a sufficient basis for acceptance. In addition, interorganizational cooperation efforts, for example with universities, for an exchange of experience and knowledge on the subject of process mining, would prove useful. An example of this is the concept of the Celonis company, which aims to disseminate and deepen process mining know-how at an international level by awarding Academic CoE Awards and promoting related initiatives.

4.4 Success factors

Success factors are critical to realizing the potential through process mining, whether in implementation or operational use.

Critical success factors for the public sector are the high costs as well as the know-how of the employees. In order to obtain the necessary know-how to cope with the complexity, both, during implementation and operation, three factors are crucial (Mamudu et. al, 2022):

- Close collaboration with vendors or consultants.
- The continuous education and training of employees.
- The recruitment of new employees with the appropriate expertise.

If these criteria are observed, it is very likely that a corresponding benefit can be generated from the costs of the process mining deployment.

Another important success factor is the data preparation in the context of the introduction of process mining in the district office. The preparation causes an enormous effort, which is why the support of vendors or consultants is of great importance. Consistently performed data preparation ensures both the data quality and the completeness of the data and the determined process model. Both are important success factors, in addition to the know-how of the employees, in order to avoid misinterpretations in operational use. Furthermore, the problem of data protection should not be neglected when using process mining.

A positive side effect from this cooperation can be a positive commitment of the employees to the topic of process mining. In conclusion, it is shown that process mining is absolutely focused on increasing efficiency and does not aim at performance evaluation and control of employees. The aforementioned integration into the organizational hierarchy also reinforces this commitment (Mamudu et al., 2022).

5 DISCUSSION

Based on the results of the expert interviews and the case study presented in the previous chapter and taking into account the theoretical background knowledge from chapters 2 and 3, the potentials of process mining for the public sector are derived. In addition to the potentials, it is also presented how the potentials can be exploited. Furthermore, trends and perspectives of process mining with the resulting benefits are analysed in more detail.

The basis for the suitability of process mining is its ability to automatically map existing processes on the basis of an event log and thus make them transparent. It proves to be important in advance to design relevant key figures and suitable forms of information representation in addition to the actual process representation. If this is done in a sufficient manner and the procurement of relevant data for the event log is ensured, the AS-IS analysis used in the context of discovery enables objectivity through intersubjective verifiability: Corresponding information does not have to be obtained by questioning those directly affected, who are subject to subjective impressions and possibly perception distortions. As a rule, it proves to be a gain in knowledge for those responsible as to how the processes are "lived" or how many process variants exist. Corresponding analyses of the actual state, for example, for bottlenecks, process variations and cause-effect relationships form the starting point for optimization considerations. This associated efficiency increases when the data basis is not just samples, but the population of cases (Munoz-Gama et al., 2017).

One framework condition is to ensure proper and responsible handling of data and its digital capture in accordance with the General Data Protection Regulation (GDPR). In this context, the possibilities for pseudonymization and anonymization must be examined. If these can be realized with a justifiable effort, data and their evaluation possibilities with process mining represent a valuable resource.

Furthermore, conformance checking and enhancement can be used in public administration. However, it must be ensured that the main variant is not adopted unreflectively as a target model. Rather, expert interviews must be conducted to clarify how automatically identified rule violations are to be dealt with. Necessary enhancements in terms of compliance open up the possibility of performing an automated check of the separation of functions, the dual control principle and fraud detection.

A cross-agency process mining application would make it possible to perform a benchmarking based on activities and their duration in a data-supported manner. Doing so, additional criteria can be defined as framework conditions and related to each other to determine whether a direct comparison is possible or justified. A limitation in this context is that different regulations (e.g., in the individual federal states) make a comparison difficult or even forbid it.

The potential of process mining must also be appreciated in that it can promote thinking in terms of and the design of processes: Managing processes is an enduring approach that requires transparency and is ideally based on current data. This proves to be the basis for effective and efficient design decisions and policy setting. Process mining offers a holistic concept for this with discovery, conformance checking and enhancement.

5.1 Recommended Actions

The following subchapter presents possible recommendations for action that emerged from the collaboration with the district office during the case study and the interviews.

Based on the given fundamentals in German public institutions, it becomes apparent that more needs to be invested in technical equipment and IT. In today's world, where everything revolves around Big Data, employees depend on powerful computers to bring appropriate added value.

Duplicate work is very time consuming. With double entry, you are doing the same activity twice, which is too much to do once to be efficient. By providing all media digitally, the amount of duplicate paperwork can at least be reduced. This also reduces the number of media changes. Furthermore, changing media is not only too time-consuming, but also prone to errors. Serious errors can occur during transmission.

Standardizing the processes to create a uniform way of working, so that, for example, a person can only be created once, can eliminate many clumsiness. In addition, an at least partially standardized way of working is important in order to be able to network with companies, as they rely on internal data.

Employees need to be prepared for the new technologies and reduce their behavioural insecurities. From the interviews, many employees are afraid of the unknown and therefore tend to be resistant to new programs or technologies, because they are not used to anything else. In addition, more attention should be paid to a diverse workforce with different skill sets. The applicant portfolio should include more technical expertise and thus recruit people who are tech-savvy. Workplace design is another area where much can be improved. Workplace models such as home offices and coworking spaces are desired alternatives to the traditional office.

In addition, it is advisable to seek more interdisciplinary recommendations and not just look to the RKI as a source and directive. There are also institutions at the state and local levels whose recommendations can be adopted. These are more likely to be networked with the district administrations and can also make individual recommendations.

Another important point is to try to improve the customer experience. The important thing here is to revise and improve existing concepts. If no customer experience concept exists, one should be created. The various touchpoints through which the citizen comes into contact with the district office must be analysed and then prepared in such a way that they offer the citizen a good customer journey.

5.2 Potentials of process mining

Process mining offers various starting points for public relations work in institutions, for example, in the areas of administration or in the context of an internal audit of activities. The basis for this is the ability of process mining to identify existing processes. Likewise, compliance auditing offers potential. Furthermore, the AS-IS analysis of processes by process mining enables objectivity, since the information is not obtained by questionnaires and interviews, which are subject to subjective influences and at the same time cause more effort.

An administration can benefit from process mining in different ways. Basically, process analysis with process mining offers the possibility to validate contents of conducted interviews in the context of an internal audit. Also, process analysis with process mining can be used to identify the different process variants, which creates transparency, which in turn supports audit preparation. In addition, automated and standardized execution is made possible. Consequently, it gains speed and the effort is reduced.

A particular potential is offered by the possibility of examining the population of cases and not limiting oneself to random samples. Specifically, this offers potential for testing the separation of functions, the dual control principle and fraud detection. An advantage with respect to fraud detection is that patterns of behaviour and unusual execution times can be identified. Likewise, process mining offers potentials for compliance, as correlations can be established between individual unobjectionable steps, that in total represent a rule violation.

In addition, process times can be quantified, which enables benchmarking of processes. The potential of process mining for management results from the formulation of processes and guidelines. Here, process mining can unfold potentials, since process formulation is an iterative process, in which discovered process deviations can lead to changes in the process description. Likewise, preventive work can be done in the public sector, for example, by having department heads use process mining to check process compliance in their department. In addition, a benefit can arise when documentation requirements for process steps are necessary (e.g., in quarantine). This proof can also be provided with process mining.

Many of the described potentials for management can also be transferred to other areas such as internal auditing. For example, the ability to investigate bottlenecks. Employees can also validate and evaluate information about the organization and processes provided by the district office. Other potentials include an effective review of missing units due to the transparency created.

Optimization potentials result from the fact that process mining can be applied to all processes. In addition, process mining thus replaces traditional instruments such as interviews, questionnaires and workshops. Analyses using process mining are faster, more transparent, more detailed and more objective. Process mining forms the starting point for a process optimization by the possible analysis of the actual situation and thus supports different process optimization philosophies. Cause-effect relationships of process weaknesses can also be analysed. Furthermore, process variations (deviations and inefficiencies) are visualized, which leads to a higher commitment of the employees to the optimization.

After the measures for a specific optimization have been implemented, process mining offers the possibility to monitor and benchmark the processes in order to identify further optimization potential if necessary. Another starting point is the quantification of throughput times. Bottlenecks and delays can be identified and improvements initiated, leading to cost savings and efficiency gains. The transparency gained about the actual situation, can also be integrated into concepts such as Lean Management and Six Sigma. The transparency created for reengineering in the context of Business Process Reengineering (BPR) is also a potential of process mining. Finally, the continuous and dynamic use of process mining can also be evaluated as an advantage compared to the one-time use of a consulting company for improvement (Van der Aalst & Weijters, 2004).

5.3 Prerequisites for process mining

The basis for process mining are event logs stored in information systems. Often, several information systems are in use simultaneously for different requirements, generating temporary and permanent traces (Beheshti et al., 2016, p. 128). The project of creating the greatest possible transparency of one's processes is therefore a difficult undertaking. Organizations are often faced with the challenge of bringing together the large amount of scattered data and generating valid recommendations for action from it. The importance of the data in information systems varies from company to company. Burratin (2015, p. 59) characterizes the concept of process awareness in two aspects. A distinction is made between the process awareness of an organization, that practices process management on a daily basis, and the process awareness of the information systems used. In the case of the latter, the question is whether the existing information systems are suitable for process-related use.

In medium and large organizations, the process culture has become established, and the information systems support process execution in its entirety. In contrast, in smaller institutions, administrative systems for handling all activities are not yet widespread. Work steps that are not recorded in systems are also referred to as shadow activities. These activities are documented in the traditional way on paper. This is for economic reasons, as information systems are expensive to both implement and record, making process mining often irrelevant to small businesses. Thus, the complete digital recording of work steps is simply not profitable.

In information systems, event data exist in a large body of forms. When processed, these can result in overwhelmingly large event logs with many attributes. Others do not even meet the minimum requirements. Event logs that do not map the minimum requirements are not suitable for process mining (Burratin, 2015, p. 4, 59). To address this, there needs to be an organization-wide understanding of the importance of proper and responsible data handling and collection. However, most data still exist in unstructured form, so one of the biggest challenges for district offices in the future will be to unite the masses of data stored in their information systems with the dynamic world of processes to gain valuable information and insights. Reliable input of log data is critical to the quality of process mining (Van der Aalst, 2016, p. 4). It is important to instil a culture, that event data should be considered as a valuable resource. High quality information has precise semantics, is reliably accurate and complete. They also take security considerations into account when recording. Data is classified into five maturity levels in the process mining Manifesto (Van der Aalst, 2012). The higher the maturity level, the more targeted event data can be used for process mining. To improve data quality in organizations, control fields are conceivable that display all necessary information and must be confirmed again by the employees involved. This can reduce erroneous data. The latter can happen with incomplete data that events do not explicitly refer to process instances.

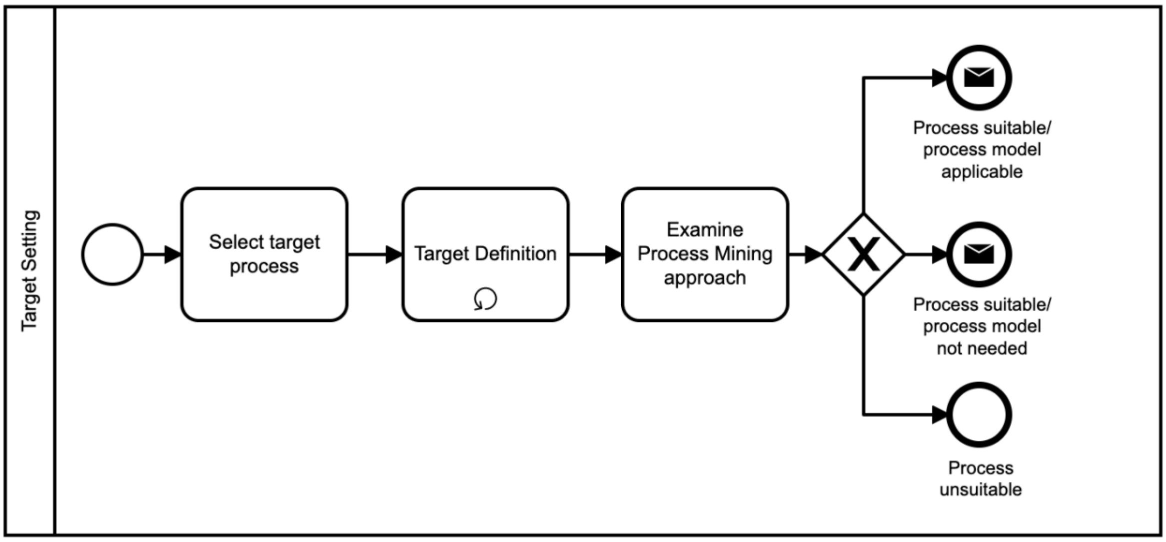
5.4 Using real time for operational support

Usually performed with historical data, process mining analyses activities that have already been completed in order to make processes more robust and efficient for cases that may arise in the future. Real-time updating of data sources and sufficiently high computational power to analyse individual activities and cases, continue to grow expectations for the tool-based method. Real-time monitoring of lead times is just one of many approaches to decision support. This online decision support directly shows deviations to employees, who can then take targeted measures. Signal messages for this already exist, but their use for operational support could be intensified in the future (Van der Aalst, 2016, p. 304). Potential is also seen for predictions and even recommended actions for ongoing cases from process mining. Cases should be accompanied there over the entire process runtime (Eck et al., 2015). For learning predictions, historical information is combined with current information (Van der Aalst, 2016, p. 301). Consistently high computing power to link real-time data and always high quality of the underlying data are prerequisites for this (Eck et al., 2015). It can be assumed, that the application of process mining in real time for operational support will initially be implemented by large organizations (Burratin, 2015, p. 4).

5.5 Suitability of process mining

Before using process mining, it is necessary to have a realistic objective that one wants to achieve by using a related software. Therefore, it proves to be useful to define suitable goals or questions. In this context, it must be clearly formulated how the technology is going to be used and whether a process model already exists. Based on the goals and the criteria mentioned, the appropriate process mining approach can then be derived. This is shown in Figure 17. For example, one can limit oneself to discovery or choose an integrated approach consisting of discovery, conformance checking and enhancement.

Figure 17: Procedure for defining the target process



Source: own work based on Morelli and Noe (2021).

Furthermore, it makes sense to examine the process-related capabilities of the respective area of public administration. Process mining benefits from a solid, digitally oriented process and data infrastructure (Van der Aalst et al., 2012, p. 179). If an institution has only low capabilities in this environment, these should first be built up through training and persuasion.

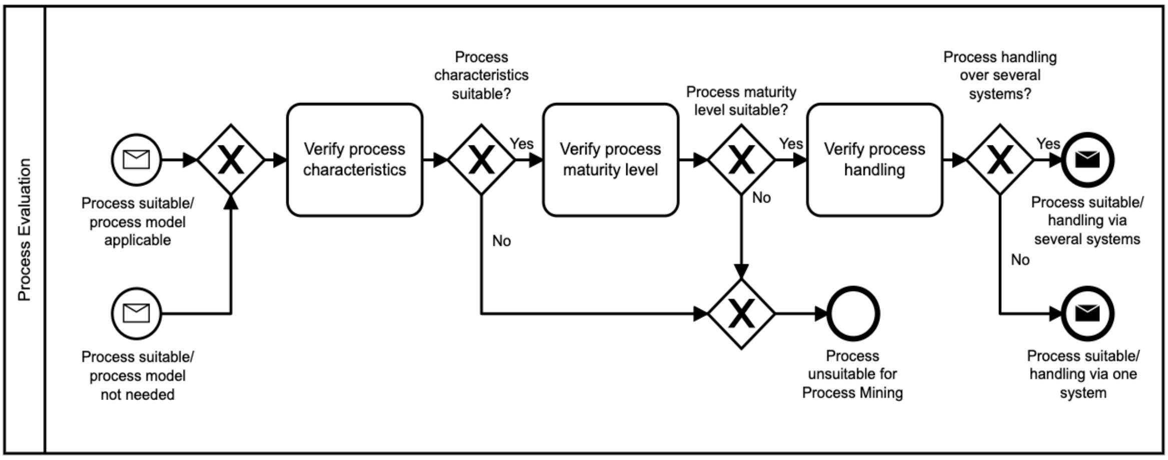
Process mining focuses on process analysis. However, not all processes have the same relevance. Rather, they can be distinguished from one another and categorized on the basis of different process characteristics (Gadatsch, 2020, p. 7). This involves determining suitability in the sense of a pre-selection before the actual application of process mining.

One process characteristic that directly affects the applicability of process mining methods, for example, is the degree of process structuring. This determines how precisely and in detail a business process has been defined and how often it deviates from its process flow diagram (Allweyer, 2005, p. 65). However, if so-called concept shifts are incorrectly identified as process deviations, this leads to an incorrect interpretation of the process mining model. For example, long waiting times in an advice hotline on COVID-19 could encourage citizens to make contact by e-mail in the future. This has the effect of shifting the concept of the process, since contacting by e-mail is now no longer a deviation, but a new form of target process handling. If it is not known that this is a concept shift, there is a risk of misinterpretation. Known concept shifts must therefore be considered when considering the model (Hierzer, 2017, p. 90).

Maturity models can be used to evaluate the suitability of a process for process mining (Becker et al., 2009, p. 249). For this purpose, their processes are classified into defined levels on the basis of specific process goals and characteristics (Bürgin, 2007, p. 46). For example, the 5-level maturity model presented in the process mining Manifesto can be used to evaluate the prerequisites (Van der Aalst et al., 2012): At level 1, recorded events sometimes do not correspond to reality, while other events are missing. In contrast, at the fifth level, event logs are characterized by automatic, systematic, and reliable recording. Data protection and security aspects are adequately taken into account. The higher the maturity level, the more specifically event data can be used for process mining.

Other approaches are available, such as the Digital Readiness Assessment Maturity (DREAMY) maturity model (Carolis et al., 2017). In general, these are extensions of the Capability Maturity Model Integration (CMMI), that incorporate aspects of digitization or process mining into the assessment of maturity levels. The process objectives and process characteristics of the individual maturity levels can be used as a benchmark. Figure 18 illustrates how the evaluation of the process could look like.

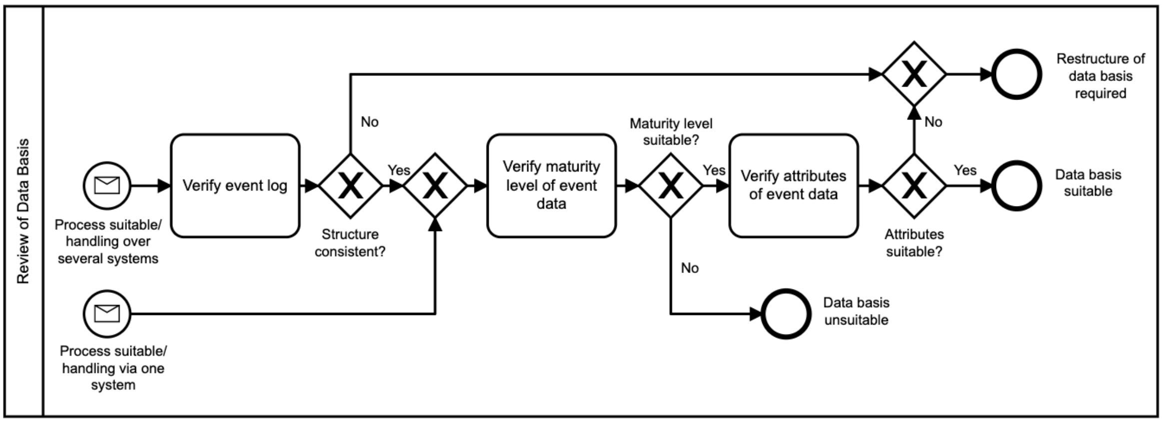
Figure 18: Activities for the evaluation of the process basis



Source: own work based on Morelli and Noe (2021).

Even if it is assumed that there is a sufficient data basis, this aspect must not be disregarded before starting an implementation project. In this case, the relevant attributes (as a minimum, case ID, activity and timestamp must be specified) must first be identified, brought together, and structured in a uniform granularity (Hierzer, 2017, p. 89; Van der Aalst 2016, p. 449). Figure 19 shows a procedure for evaluating the data basis.

Figure 19: Process steps to evaluate a data base



Source: own work based on Morelli and Noe (2021).

Missing prerequisites resulting from the above three approaches can be interpreted as identified fields of action to make public administration process mining capable.

In summary, the processes described above are intended to provide clues, as to when or whether the use of process mining makes sense for a specific use case in public administration. For the identification of the central building blocks in terms of a framework, three different perspectives are treated, which can also be interpreted as a phase concept (Morelli & Noe, 2021): the first step comprises requirements relevant for the target identification process. This is followed by the analysis of the process structure. The third phase deals with the data basis of the business process under consideration. Based on the respective perspective, the associated procedure is visualized and converted into a modular structure. The process models presented below have been modeled using BPMN 2.0

5.6 Organization and data origin

The organizational structure should support the potentials of process mining for the public sector and the associated optimization in the best possible way. For this purpose, the establishment of a staff position appears to be the best possible integration into the organizational structure. Likewise, the technical responsibility should be coordinated by this central office together with the IT department. With this structure, duplicate solutions and thus unnecessary costs can be avoided. Technical issues can be coordinated between the staff unit and the IT department in a targeted manner. In addition, the establishment of a staff unit creates a clear point of contact in the district office. The support of process mining on the part of the management is clearly signalled by this structure, whereby a high level of commitment can be achieved.

In addition to hierarchical placement, the user group is of particular importance. It is recommended that the user group for process mining is large. However, there are differences in the application domains. On the one hand, an extension of the user group is only possible to a limited extent in the application for public institutions, since these activities concern a limited number of employees. However, an application by the department heads in the context of a preventive implementation is also conceivable here. On the other hand, the circle of process mining users can be expanded nationwide with the goal of analysing and optimizing processes. An added value resulting from a large number of users of process mining software is that a lot of know-how is built up within the company's own ranks. In addition, experience can be gained that leads to a broad support of process mining.

The use of the different types of process mining depends on the specific use case. In order to exploit the full potential, the goal should be to use process mining as an operational IT support.

Furthermore, it can be stated that with respect to the data origin, all systems that automatically collect event data are conceivable. The explicit sources are determined by the process under investigation. The system architecture specifies the data preparation process, that is also whether an extractor is sufficient or whether a data lake or a data warehouse should be used. To check the completeness and resilience of the data, the plausibility checks used in practice are recommended during implementation. The formulation of quality guidelines or the evaluation of maturity levels, on the other hand, is not necessary. The cross-system used generates enormous potentials that no other tool can offer.

In order to realize this added value, the additional effort that arises from the inclusion of several systems should be accepted. The use of process mining only makes sense if it is carried out by several institutions. In order to cover the costs and the effort, a cooperation regarding the systems and licenses of the process mining technology between the federal government, the state and the municipality is necessary.

5.7 Inter-organizational process mining

In today's work environment, an increasing interconnection of existing networks can be observed, for example in companies. A well-known example for these collaborations is car manufacturers and their suppliers. Here, information systems of suppliers are directly linked to those of car manufacturers in order to be able to guarantee just-in-time delivery, which is so important for the automotive industry. In other cases, car manufacturers even make it a condition that their own ERP system is also maintained by the suppliers. Process mining across organizations will gain in importance in the course of this. Potentials for optimization will be enlarged to a greater extent. In this context, cost savings are not the only issue: The entire project thrives on the exchange of experience and knowledge on the subject of process mining. However, in order to contain the dilution and uncontrolled flow of technical internals, compliance with data protection regulations is mandatory.

5.8 Future prospect

The future potential for process mining is influenced by two main factors. On the one hand, it is expected that costs will decrease due to the increasing number of providers on the market, which will make its use sensible for a larger number of processes. Second, the combination with automation through Artificial Intelligence (AI) or RPA offers enormous potential for process mining. Furthermore, these are automated notifications of violations or automated checks for management. On the other hand, the combination with RPA opens up great potential for process optimization. Process mining can be used to identify processes for which the use of RPA software is conceivable. Process progressions, AI-based decisions and their effects can be tracked and understood down to individual process steps by visualizing process data from previous processes. That is how the future will bring a more flexible application of RPA (Morelli & Karkos, 2022).

Geyer-Klingeberg et al. (2018) propose on the basis of RPA application that certain key drivers are essential for a successful implementation of process mining and RPA. The maximum potential can be achieved with high manual effort and processing time. In addition, there are fixed, standardized and mature processes. The technical integration can also be more complex here. Human processing errors can be detected. Standardization must take place before automation to guarantee the highest possible success. This means that the variants of the processes must be standardized in order to generate high volumes for transactions as well. To achieve maximum results in the shortest possible time, activities must be prioritized and available resources must be targeted. For RPA, this means faster benefits can be recorded. By combining process mining and RPA, results can be continuously improved and knowledge can be acquired for future projects by using these insights. In this way, constant benchmarking of projects can also be done in order to derive the maximum benefit from automation.

CONCLUSION

Initial premise for this thesis was the digitalization of processes and the question whether process mining can be used in public administration. To this end, potentials were to be identified on the basis of an empirical study. The determination of the prerequisites for the development of these potentials as well as an in-depth analysis of the trends and perspectives of process mining, formed a further objective within this work. For this purpose, the methodological basics of process mining were clarified in a first step, and then the fields of application were explained. Likewise, an introduction into the application possibilities of process mining took place at a concrete example for the illustration. Building on the theoretical basics, the introduction to the methodological contexts of the empirical investigation followed.

Based on research of the "state of the art" of the relevant literature, relevant guidelines for the introduction of process mining are identified and the associated potentials and challenges are determined from a general perspective. Subsequently, this thesis describes the applied qualitative research methods such as conducting a case study, conducting expert interviews and prototyping, using a process mining tool. The associated objective of this methodological triangulation is to characterize and evaluate findings about the potential for use in public administration in a generalized form. Critically, this inductive approach does not allow for firm conclusions (Bryman & Bell 2011, p. 146). Moreover, the results of qualitative research are open-ended and in need of interpretation (Jonker & Pennink 2010, p. 89). However, their use seems justified to the authors, since under the circumstances under consideration the boundary between observation and context is not clearly evident and therefore the framework conditions of the phenomenon to be researched must also be included.

This involved first determining the current state of research and defining the existing research gap. The objective of the work derived from this, formed the starting point for the description of the empirical procedure of the study. Based on the theoretical assumptions, the analysis of the research results followed. The findings from the expert interviews were compared with the established theory in order to present the potential of process mining for the public sector on this basis. The results of the empirical investigation show that process mining is excellently suited for process identification and for creating process transparency. Subjective process analysis by interviews can be replaced by process mining. A carefully conducted implementation of process mining is elementary for the exploitation of the potentials. In addition, process responsibility in a staff unit as well as a large user group strengthens the commitment of the employees to process mining. Another relevance is to ensure the appropriate know-how of the employees. Considering this, these fundamentals enable the successful use of process mining for a large body of processes and generates a significant added value, the cross-system application. The effective design of process mining is of elementary importance, not least because of the currently high costs of implementation and operational use. However, it should be noted that the existing IT system architecture has a significant impact on the design of process mining and influences it massively. If it is implemented according to these criteria, it can be used effectively for a large proportion of applications. The greatest potential overall lies in the fast, objective, complete and visually prepared transparency of the existing processes. From this, deviations can be identified and analysed. In parallel, the AS-IS analyses form the starting point for extensive optimizations. Furthermore, the processes as well as the introduced optimization measures can be monitored sustainably. Process mining can thus support or complement the existing philosophies and tools of process management. In addition, there is the possibility to enrich and further develop the existing processes by process mining. In the future, the combination with AI and RPA as well as operational IT support will generate further potential for process mining.

The discussion includes a detailed description of the potential opportunities. The recommendations for implementing process mining in public administration are a central aspect of the study. These include organizational considerations, such as the creation of a CoE, to bundle the relevant skills and impulse generators as well as suggestions for a structured procedure for the introduction of this approach. As a phase-oriented concept, the steps "definition of the target area", "definition of the process basis and the data basis" are characterized in each case with associated process steps.

Building on the findings of the empirical study, starting points for further research could be uncovered. The challenges and success factors are a multi-layered topic that has an immense influence on the success of process mining. Furthermore, the combination with AI and RPA offers enormous potentials that should be investigated in more detail. The underlying empirical investigation is subject to limitations associated with methodological restrictions, but also with the generally limited generalizability. A weakness of the inductive approach in terms of research methodology and analysis methods is the uncertain conclusion (Bryman & Bell, 2011, p. 146).

In addition, the results of qualitative research are open-ended and in need of interpretation. Qualitative research methods offer a large pool of opportunities and possibilities, yet this type of methodology and the semi-structured expert interviews must be viewed critically (Jonker & Pennink, 2010, p. 89). First, because of the imprecise distinction between facts and interpretation of results, and second, the researcher as interviewer puts a subjective position that influences the results. Finally, the sample of four interviews and the heterogeneous composition is informative and gave a clear as well as comprehensive insight into the topic area. Yet further interviews could have additionally validated the findings.

Once the prerequisites for the use of process mining have been met to a sufficient degree, a process culture must be established that ensures sufficient acceptance. In the sense of the change management approach, fears of a related change must be eliminated among those affected. It must be conveyed, that process mining is not aimed at performance evaluation and control of individual employees, but rather at overarching increases in effectiveness and efficiency.

As an organizational solution for implementing the process mining approach in the public sector, the use of a CoE solution appears to be suitable to ensure sufficient coordination. The CoE is responsible for data security, quality, governance and compliance. Collaborative knowledge is permanently conveyed with the help of best-practice guidance and training and is aligned with overarching goals (Beuckes & Liesert, 2019).

With regard to the interaction of different CoEs in the decentralized structures of public administration, a stronger shift toward hybrid organizational forms appears desirable. The hybrid model is a mix of centralized and decentralized approaches, as is often found in business practice, but less so in public administration. A cross-agency process mining deployment would allow benchmarking based on activities and their duration. Automation facilitates intersubjective verifiability (Beuckes & Liesert, 2019).

In general, inter-organizational cooperation efforts, for example with universities, are useful for an exchange of experience and knowledge on the topic of process mining. One example is the concept of the company Celonis, which wants to spread and deepen process mining know-how on an international level by awarding academic CoE awards and promoting related initiatives (Beuckes & Liesert, 2019).

Process mining will continue to gain importance in the coming years and in the near future. This can be assumed due to the digital transformation and the increasing amount of event data. Almost 80 % of companies in Germany are focusing on digitization. Of these companies, 90 % in turn believe that process mining, among other things, will play an essential role in future projects (Reder, 2019).

To accelerate analyses with process mining in the future, AI-based approaches and machine learning will increasingly come to the fore. Insights and predictions for the future will be derived from historical data. Furthermore, operational support, which enables real-time monitoring of running processes, will also become increasingly important as additional functionality. Process mining will tend to be available to users not only in the form of a pure stand-alone technology but can also be integrated as an additional component in other software (Popovic, 2020).

Fairness and causality analysis of process data will be given greater importance in process mining. This relates to the protection of confidential data and accountability for compliance violations. No one should be hastily held accountable for errors, because often the simple correlation of individual variables is not sufficient evidence of a compliance violation. Rather, the true causality behind certain variables must be investigated and made transparent to avoid correlation errors (Van der Aalst, 2019).

Process mining can be used to investigate other myriad research questions. Data sets from other institutions can be considered. Each institution may formulate a different research question or research objective. In addition, more in-depth analysis of individual processes can be performed to obtain more detailed results. Overall, process mining offers a wide range of analysis and research interests.

In conclusion, this work provides a solid foundation for the potentials of process mining for the public sector, which can be further built upon. Further questions could deal with the concrete design of the uncovered potentials or with the potentials for other application areas. In addition, the research to date, offers starting points for quantitative research, especially on the application of the identified potentials in public administration as well as on the derived success factors and challenges. Furthermore, the integration of process mining into the existing architecture of other institutions could be researched quantitatively.

REFERENCE LIST

1. Allweyer, T. (2005). *Geschäftsprozessmanagement*., W3L-Verlag Herdecke.
2. Beheshti, S., Benatallah, B., Sakr, S., Grigori, D., Motahari-Nezhad, H. R., Barukh, M. C., Gater, A. & Ryu, S. H. (2016). *Process Analytics: Concepts and Techniques for Querying and Analyzing Process Data.* Springer.
3. Bergman, B. & Klefsjö, B. (2010). *Quality from Customer Needs to Customer Satisfaction*. Studentlitterature AB.
4. Becker, J., Knackstedt, R. & Pöppelbuß, J. (2009). Entwicklung von Reifegradmodellen für das IT-Management. *Wirtschaftsinformatik und Angewandte Informatik*, *51(3),* 249–260. https://doi.org/10.1007/s11576-009-0167-9.
5. Beuckes, T. & Liesert, H. (2019). *Beyond RPA: Intelligente Prozessautomatisierung Auf dem Weg zum großflächigen Einsatz*. https://docplayer.org/168503848-Beyond-rpa-intelligente-prozessautomatisierung-auf-dem-weg-zum-grossflaechigen-einsatz.html.
6. BMWK (2021, December 27). *Digitale Agenda*. https://www.bmwk.de/Navigation/DE/Themen/themen.html?cl2Categories_LeadKeyword=digitale-agenda.
7. Bryman, A., Bell, E. & Harley, B. (2018). *Business Research Methods*. Oxford University Press.
8. Buck-Emden, R., & Dahmann, F. D. (2018). Analyse von Studienverläufen mit Process-Mining-Techniken. *HMD Praxis der Wirtschaftsinformatik, 55(4)*, 846-865.
9. Burattin, A. (2015). Process Mining Techniques in Business Environments. In *Lecture notes in business information processing*. Springer Science+Business Media. https://doi.org/10.1007/978-3-319-17482-2
10. Bürgin, C. (2007). *Reifegradmodell zur Kontrolle des Innovationssystems von Unternehmen*. ETH, Zürich. https://doi.org/10.3929/ethz-a-005486187
11. Carolis, A. D., Macchi, M., Negri, E. & Terzi, S. (2017). A Maturity Model for Assessing the Digital Readiness of Manufacturing Companies. In *IFIP Advances in Information and Communication Technology* (p. 13-20). Springer Science+Business Media. https://doi.org/10.1007/978-3-319-66923-6_2.
12. Celonis SE (2021). *What is Process Mining?.*Retrieved April 2, 2022 from https://www.celonis.com/process-mining/what-is-process-mining.
13. De Weerdt, J., Schupp, A., Vanderloock, A., & Baesens, B. (2013). Process mining for the multi-faceted analysis of business processes - A case study in a financial services organization. *Computers in Industry, 64*(1), 57-67. https://doi.org/10.1016/j.compind.2012.09.010
14. Eck, M. L. V., Lu, X., Leemans, S. J., & Van Der Aalst, W. M. (2015). PM2: a Process Mining project methodology. *Science & Engineering Faculty*. https://eprints.qut.edu.au/107398/.
15. Gadatsch, A. (2020). Grundkurs Geschäftsprozess-Management. In *Springer eBooks*. https://doi.org/10.1007/978-3-658-27812-0.

16. Gemmel, G. (2014). Strategisches Informationsmanagement in Großprojekten der Industrie. In *Springer eBooks*. https://doi.org/10.1007/978-3-662-43423-9.
17. Geyer-Klingeberg, J., Nakladal, J., Baldauf, F., & Veit, F. (2018). *Process Mining and Robotic Process Automation: A Perfect Match*. Celonis SE. https://ceur-ws.org/Vol-2196/BPM_2018_paper_28.pdf.
18. Greasley, A. (2019). Simulating Business Processes for Descriptive, Predictive, and Prescriptive Analytics. *De Gruyter eBooks*. https://doi.org/10.1515/9781547400690.
19. Ha, S. H. & Lee, M. J., 2010. Customer service quality improvement in the public sector through the Internet. *Total quality management & business excellence, 21*(11), 1161-1176. https://doi.org/10.1080/14783363.2010.529341
20. Hierzer, R. (2020). *Prozessoptimierung 4.0: Den Digitalen Wandel als Chance nutzen* (2nd ed.). Haufe Group.
21. Jonker, J., & Pennink, B. (2010). *The Essence of Research Methodology: A Concise Guide for Master and PhD Students in Management Science*. Springer Science & Business Media.
22. Kaiser, R. (2014). *Qualitative Experteninterviews*. Springer-Verlag.
23. Leno, V., Dumas, M., Maggi, F. M., & La Rosa, M. (2018). *Multi-perspective process model discovery for robotic process automation*. University of Tartu. https://ceur-ws.org/Vol-2114/paper5.pdf
24. Li, J., Wang, H. J., & Bai, X. (2015). An intelligent approach to data extraction and task identification for process mining. *Information Systems Frontiers, 17*(6), 1195-1208.
25. Lindenbach, H., & Göpfert, J. (2012). *Geschäftsprozessmodellierung mit BPMN 2.0: Business Process Model And Notation*. Oldenbourg Verlag.
26. Lück-Schneider, D. (2016). Process-Mining in der öffentlichen Verwaltung. *GI-Jahrestagung,* 659–670.
27. Maleyeff, J., & Campus, H. (2007). *Improving Service Delivery in Government with Lean Six Sigma*. Washington, DC: IBM Center for the Business of Government.
28. Mamudu, A. O., Bandara, W., Wynn, M. T. & Leemans, S. J. J. (2022). A Process Mining Success Factors Model. In *Lecture Notes in Computer Science* (p. 143–160). Springer Science+Business Media. https://doi.org/10.1007/978-3-031-16103-2_12
29. Manfreda, A., Buh, B., & Štemberger, M. I. (2015). Knowledge-intensive process management: a case study from the public sector. *Baltic Journal of Management, 10*(4), 456–477. https://doi.org/10.1108/bjm-10-2014-0170
30. Morelli, F. & Karkos, F. (2022). Entwicklung eines Vorgehensmodells zur Nutzung von Process Mining für die Auswahl und Anwendung von RPA-Lösungen zur Optimierung von Geschäftsprozessen. *Anwendungen und Konzepte der Wirtschaftsinformatik, 16*, 14. https://doi.org/10.26034/lu.akwi.2022.3404.
31. Morelli, F. & Noe, F. (2021). Process Mining. *WISU (11),* P. 1206-1232.
32. Munoz-Gama, J., Rojas, E., Sepúlveda, M., Capurro, D., Traver, V., & Fernandez-Llatas, C. (2017). Question-driven methodology for analysing emergency room processes using process mining. *Applied Sciences, 7*(3), 302.
33. Peters, R., & Nauroth, M. (2019). *Process-Mining*. Springer Gabler, Wiesbaden.

34. Popovic, A. (2020). *Process Mining is the key to effective RPAs*. Celonis. https://www.celonis.com/blog/securing-rpa-through-process-mining/.
35. Prostean, G., Villahoz, J. J. L., Brancu, L., & Bakacsi, G. (2020). *Innovation in Sustainable Management and Entrepreneurship*. Springer International Publishing.
36. Reder, B. (2019). Process Mining und Automatisierung sind Schlüsselelemente der Digitalisierung. *Computerwoche*. https://www.computerwoche.de/a/process-mining-und-automatisierung-sind-schluesselelemente-der-digitalisierung,3547348.
37. RKI. (2021). *DEMIS - Deutsches Elektronisches Melde- und Informationssystem für den Infektionsschutz*. https://www.rki.de/DE/Content/Infekt/IfSG/DEMIS/DEMIS_node.html.
38. Salzmann, O. (2019). Process Mining im Reality Check. *ManagerWISSEN, 2019*(6). https://www2.deloitte.com/de/de/pages/finance/articles/process-mining.html.
39. Saunders, M., Lewis, P., & Thornhill, A. (2019). Research Methods for Business Students, 8th ed. In *Pearson eBooks*. http://dspace.uniten.edu.my/handle/123456789/18304.
40. Schönig, S. (2015). *Ein Process Mining-Rahmenwerk für agile, personenbezogene Prozesse* (Doctoral dissertation). University Bayreuth Germany.
41. Sprondel, W. M., & Grathoff, R. (1979). *Alfred Schütz und die Idee des Alltags in den Sozialwissenschaften*. Ferdinand Enke Verlag.
42. Suriadi, S., Andrews, R., Hofstede, A. H. M., & Wynn, M. T. (2017). Event log imperfection patterns for process mining: towards a systematic approach to cleaning event logs. *Information Systems, 64*, 132-150. https://doi.org/10.1016/j.is.2016.07.011.
43. Thomas, G. (2021). *How to do your case study*, *3rd ed*. SAGE Publications Limited.
44. Van der Aalst, W. (2011). *Process Mining: Discovery, Conformance and Enhancement of Business Processes.* Springer.
45. Van Der Aalst, W. (2012). Process Mining: Overview and Opportunities. *ACM Transactions on Management Information Systems (TMIS), 3*(2), 1-17.
46. Van der Aalst, W. (2016). *Process Mining: Data Science in Action.* Springer.
47. Van der Aalst, W. (2019, April 3). *Celosphere Keynote Live (Part One)* [Video]. YouTube. https://www.youtube.com/watch?v=yyts_srs_zc&t=1h4m50s.
48. Van der Aalst, W., & Dustdar, S. (2012). Process Mining Put into Context. *IEEE Internet Computing, 16*(1), 82-86. https://doi.org/10.1109/mic.2012.12
49. Van der Aalst, W., & Weijters, A. (2004). Process Mining: a research agenda. *Computers in Industry, 53*(3), 231-244. https://doi.org/10.1016/j.compind.2003.10.001
50. Van der Aalst, W., Adriansyah, A., Medeiros, A. K. A. D., Arcieri, F., Baier, T., Blickle, T., … & Wynn, M. (2012). Process Mining Manifesto. In *Springer eBooks* (S. 169–194). https://doi.org/10.1007/978-3-642-28108-2_19
51. Van der Aalst, W., Bichler, M., & Heinzl, A. (2018). Robotic process automation. *Business & Information Systems Engineering, 60*(4), 269-272.
52. Van der Aalst, W., Rubin, V., Verbeek, H. M. W., van Dongen, B. F., Kindler, E., & Günther, C. W. (2010). Process Mining: a two-step approach to balance between underfitting and overfitting. *Software & Systems Modeling, 9*(1), 87-111.

53. Vignali, G., Ryding, D., Vignali, C., Feraco, A., & Vranesevic, T. (2011). *An Essay Approach Marketing Research Thinking*. Access Press.
54. Ward-Dutton, N. 2020. From Big Boxes to Intelligence Everywhere: The Changing Face of Automation. In *Hyperautomation,* p. 18-37, BookBaby.
55. Yin, R. K. (2018). *Case Study Research and Applications*. SAGE Publications.
56. Zahorsky, I. (2018, March 21). Mit Process Mining zu einem bürgernahen öffentlichen Sektor. *eGovernment*. https://www.egovernment-computing.de/mit-process-mining-zu-einem-buergernahen-oeffentlichen-sektor-a-695494/

APPENDICES

Appendix 1: Summary

Poslovne procese je vedno možno izboljšati, pri čemer ni enostavno poiskati področij za izboljšave in izboljšave tudi uvest. Potrebe strank in poslovni modeli se razvijajo hitreje kot kdaj koli prej. Organizacije niso prepričane, ali se bo pričakovani učinek izkazal tudi po obsežnih pripravah. Zato mora vsaka organizacija svoje procese redno ocenjevati in izboljševati. V tej situaciji je lahko uporabna nova tehnologija procesnega rudarjenja.

Počasno in nezadostno delovanje javnega sektorja je pomemben vzrok nezadovoljstva državljanov (Maleyeff & Campus, 2007). Državljani postanejo nezadovoljni, ko njihove želje in pričakovanja niso izpolnjeni. Zato tudi organizacije javnega sektorja pogosto skušajo ponujati storitve oziroma izvajati procese tako, da izpolnjujejo pričakovanja svojih strank. Po Bergmanu in Klefsjöju (2010) so ti procesi namenjeni preoblikovanju administrativnih vložkov v določene rezultate, ki ugajajo strankam. Občinske organizacije morajo zato nenehno pregledovati in izboljševati svoje procese, da bi zadovoljile zahteve in želje svojih strank.

Tudi v javnem sektorju je prisoten občutek nujnosti in pomembnosti izboljšav procesov, saj ljudje ne bodo tolerirali slabo izvedenih storitev (Ha & Lee, 2010). Vsaka institucija lahko izboljšuje procese s pomočjo procesnega rudarjenja. Ključni kazalniki učinkovitosti se lahko uporabijo za vizualno prepoznavanje in spremljanje morebitnih odstopanj od želenega postopka. Možno je poiskati skrita, prej neidentificirana ozka grla, pomanjkljivosti in z njimi povezane stroške ter možnost nadaljnje avtomatizacije. Procesno rudarjenje temelji na različnih virih podatkov, ki redno ustvarjajo primere, znane kot "primeri procesa" in jim lahko uporabniki dinamično sledijo v obliki nadzornih plošč (Celonis SE, 2021). Natančne analize so dosegljive, če se uporabljajo v povezavi s ključnimi kazalniki in preverjanji skladnosti s ciljnim procesom. Procesno rudarjenje omogoča tudi iskanje ustreznih informacij in njihovo globlje razumevanje. Digitalizacija, strukturni premiki na trgu dela in demografske spremembe pomembno vplivajo na vse vidike javne uprave v Nemčiji. Nemška vlada s svojo digitalno agendo razvija okvir prihodnosti: navedeni cilj je digitalna, državljanom prijazna Nemčija z obveznimi merili za nacionalno digitalizacijo.

V obravnavanem javnem zavodu poteka zelo veliko procesov. Ti so lahko enostavni, z omejenim številom udeležencev in možnostmi odločanja, ali pa izjemno zapleteni. V tem kontekstu se pogosto pojavljajo vprašanja o odstopanjih, časih mirovanja in točnosti. Pristopi procesnega rudarjenja bodo z razvojem e-uprave neizogibno postali pomembnejši za javno upravo. Potencial tega pristopa je precejšen, zlasti pri popolnoma avtomatiziranih postopkih. Začetni izzivi, ki bodo verjetno vključevali iskanje pravih podatkov, bi morali izginiti, ko bo tehnika postajala vse bolj priljubljena. Podobno je mogoče takoj zaznati dejanske kadrovske omejitve (Lück-Schneider, 2016).

Namen te raziskave je osvetliti uporabnost procesnega rudarjenja v javnem sektorju in opredeliti pogoje, ki morajo biti izpolnjeni pred uspešno uvedbo. Poleg tega je ključna motivacija pomoč instituciji s poenostavitvijo njenih postopkov. Pridobljeno znanje bo v pomoč tudi drugim javnim institucijam, kot je občina ali oddelek za javno zdravje. Cilj je ustvariti pregled ustreznosti procesnega rudarjenja za javni sektor in prispevati k znanju o tem, kako narediti nemško javno upravo učinkovitejšo. Poleg tega je cilj tega dela ugotoviti odnos in pripravljenost javne uprave na procesno rudarjenje, ugotoviti odstopanja od načrtovanega vodenja procesa ter ovrednotiti postopek v izbrani instituciji in predlagati izboljšave.

Za dosego ciljev tega sem v magistrskem delu uporabila tako primarne kot sekundarne podatke. Kot primarni vir informacij je služilo spoznavanje postopkov posameznega javnega subjekta. Ker so bile v središču intervjujev pomembne osebe, ki sodelujejo v izbranih procesih, so bili zato najboljši način zbiranja podatkov intervjuji. Da bi bolje razumeli številne vloge in funkcije, vključene v proces, so bili intervjuji opravljeni na polstrukturiran način. Vključen je tudi scenarij uporabe procesnega rudarjenja v javni upravi. Izdelava primera uporabe v sodelovanju z javno institucijo je pomagala pri operacionalizaciji. Rezultate primarnega zbiranja podatkov sem ocenila in primerjala s predhodnimi raziskavami, s poudarkom na merilih uspešnosti implementacije procesnega rudarjenja. Na podlagi ugotovitev sem podala priporočila. Zaradi omejitev glede zaupnosti s strani institucije, ki je predmet preiskave, sem spremenila podrobnosti, kot so ime institucije in druge razkrite informacije. Za ohranitev anonimnosti sem uporabila tudi psevdonimi.

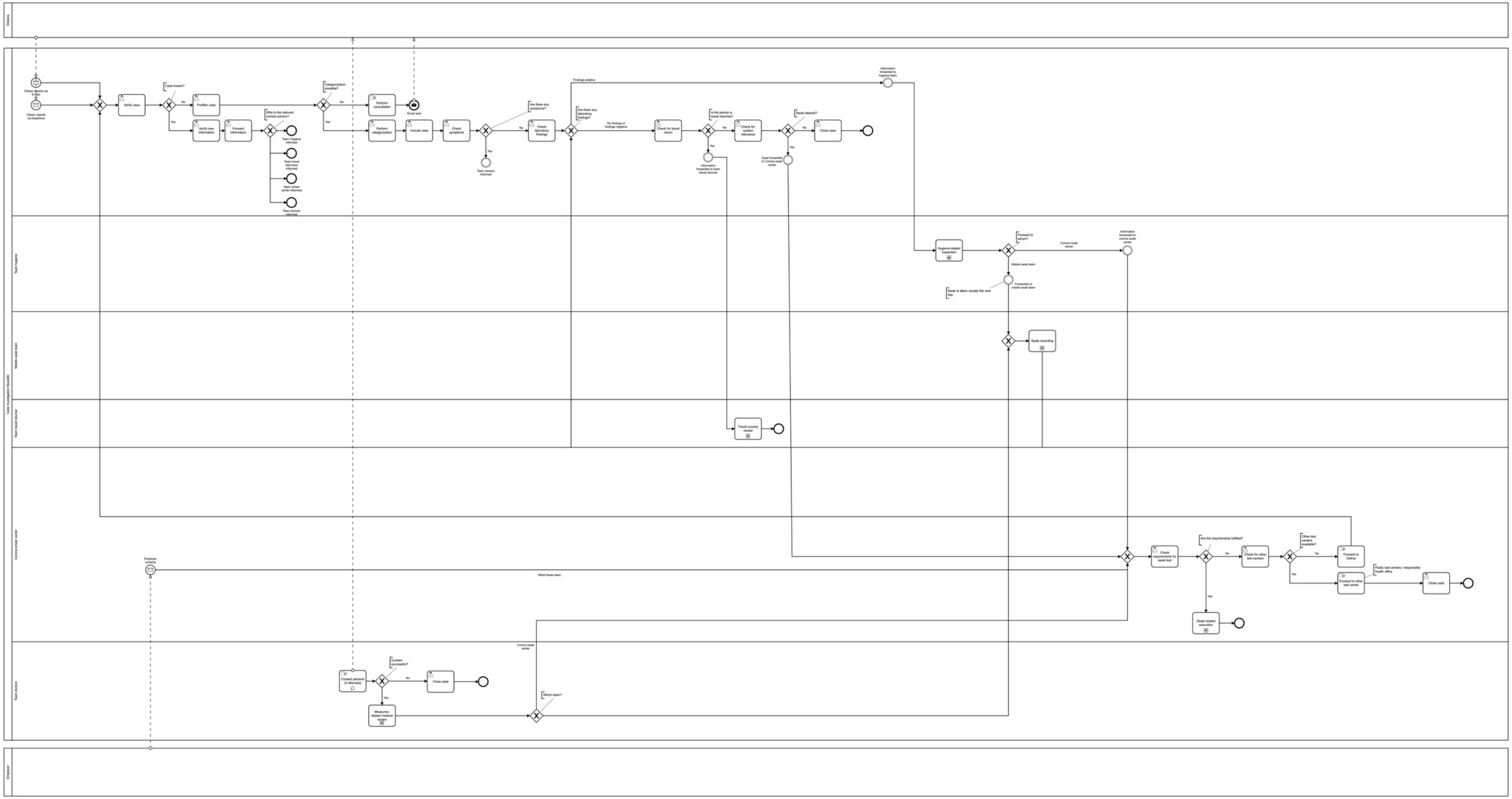
Drugo poglavje, ki sledi uvodu prvega poglavja, je sestavljeno iz teoretičnih izhodišč. To naj bi zagotovilo teoretične podlage, temeljno razumevanje teme na splošno in zadevne tehnologije. Temeljne ideje so podane skupaj s stanjem raziskav v tistem času. V tretjem poglavju so opisane tehnike zbiranja podatkov, ki se uporabljajo v aplikativnih raziskavah. V četrtem poglavju so nato predstavljene in pojasnjene ugotovitve iz prejšnjega poglavja. Peto poglavje, ki je pred zaključkom, govori o ugotovitvah in ponuja nekaj predlogov za izboljšave.

Ugotovila sem, da v obravnavani organizaciji na potencial procesnega rudarjenja v prihodnosti vplivata dva ključna elementa. Po eni strani se pričakuje, da se bodo stroški znižali zaradi povečanja števila ponudnikov na trgu, zaradi česar bo njegova uporaba praktična za širši obseg poslovanja. Drugič, procesno rudarjenje ima velik potencial, če je avtomatizacija kombinirana z robotsko avtomatizacijo procesov (RPA) ali umetno inteligenco. Zlasti povezava z RPA ustvarja veliko priložnosti za izboljšanje procesa. Iskanje procesov, ki bi jim lahko koristila uporaba programske opreme RPA, je mogoče izvesti s procesnim rudarjenjem. S prikazom procesnih podatkov iz predhodnih procesov je mogoče slediti in razumeti napredovanje procesov, izbire na podlagi umetne inteligence in njihove vplive do posameznih stopenj procesa. Na ta način bo v prihodnosti omogočena bolj prilagodljiva uporaba RPA.

Geyer-Klingeberg et al. (2018) so pokazali, da je za uspešno izvajanje procesnega rudarjenja in RPA potrebnih nekaj ključnih dejavnikov. Za doseganje najvišjega potenciala je potrebno veliko ročnega dela in časa obdelave. Obstajajo tudi uveljavljeni, standardizirani in sofisticirani procesi. V tem primeru je lahko tudi tehnološka integracija težja. Najdemo lahko napake pri človeški obdelavi. Pred avtomatizacijo je standardizacija nujna za zagotovitev največjega uspeha. To pomeni, da morajo biti različice procesov tudi standardizirane, če želimo ustvariti ogromno število transakcij. Aktivnosti morajo biti prioritetne in razpoložljiva sredstva ciljno usmerjena, da se zagotovijo največji učinki v najkrajšem času. To omogoča RPA, da hitreje zajame koristi. Rezultate je mogoče nenehno izboljševati z integracijo procesnega rudarjenja z RPA, informacije pa je mogoče zbrati za prihodnje projekte z uporabo teh vpogledov. To omogoča nenehno primerjalno testiranje, da kar najbolje izkoristimo avtomatizacijo.

Prihodnji obeti so podrobno opisani v diskusiji. Ključna sestavina so predlogi za uvedbo procesnega rudarjenja v javni upravi. Ti vključujejo ideje za organiziran proces za izvajanje te metode, pa tudi organizacijska vprašanja, kot je oblikovanje skupin za združevanje potrebnih talentov in generatorjev impulzov. Kot fazno usmerjen koncept sta definicija ciljnega območja ter definicija procesne osnove in podatkovne baze vsaka opisana z ustreznimi stopnjami procesa. Predstavljena so tudi področja, kjer bi bilo koristno izvesti dodatne raziskave. Kompleksnost vprašanj, povezanih s težavami in dejavniki uspeha, pomembno vpliva na to, kako dobro deluje procesno rudarjenje. Poleg tega predstavlja integracija RPA in umetne inteligence ogromen potencial, ki zahteva nadaljnjo preiskavo. Predstavljena raziskava ima tudi metodološke omejitve in običajno omejeno posplošljivost, kar prav tako predstavlja omejitev.

Appendix 2: Process COVID-19 Case Investigation



Appendix 3: Interview questionnaire

1. How long have you been working in this field and what is your exact job title?
2. What does your daily workday look like? What tasks do you take on?
3. How do you see the current process flow? What is your overall impression?
4. In your experience, where are the biggest problems?
5. Which process step do you see as difficult or complex?
6. Where is outside (external) help needed?
7. How many IT systems do you have to operate?
8. How often is information missing during the process? Is this serious information? What is the impact of the lack?
9. How often does an organizational change occur?
10. How often does a problem get bounced back and forth?
11. How often do you need to change media? (All digital?)
12. What do you think is the number of process variations?
13. Do you see any redundancies (duplicate checks, for example)?
14. Can you identify at least one or more bottlenecks in the process?
15. How high are the wait times, or waiting times? Is the lead time too high?
16. Where do you see potential for improvement?

Appendix 4: Expert Interviews

Interview question	Interviewer 1 Date: 10.05.2021	Interviewer 2 Date: 11.05.2021	Interviewer 3 Date: 11.05.2021	Interviewer 4 Date: 25.05.2021
1.How long have you been working in this field and what is your exact job title?	> Since October 2020 > Organizational and process analysis > Consulting activity	> Town clerk (administration) > Since 2005 in the Department of Hygiene and Health	> Public health specialist and head of the pandemic team	> Containment scout; senior service > Since 2020
2.what does your daily workday look like? What tasks do you take on?	Consulting	> Personnel allocation and equipment > Information forwarding > Coordination	> Conducting and leading central situation meetings > Coordinate staffs > Sufficiency of situation description > Developing perspectives for the future	> Case handling in the pandemic team > Contact person follow-up > Internal COVID-19 cases, hygiene cases
3.how, do you see the current process flow? What is your overall impression?	The development has made the process well.	> The process is now very good due to constant adjustments	> Great development of the process speaks for itself > Routine has made it better, yet it is still not error-free	good

4.where are the biggest problems according to your experience?	> Double entries in Survnet and own COVID-19 database (Access meanwhile SQL based), are entered in the reporting software > double input costs time > Digitization is not good (fax)	> No equipment (camera, headset), no home office; Little space for team meetings. > Survnet and COVID-19 database double entries > Changing personnel (every 10 days) and resulting information gaps	> Digital support of databases > All interfaces (personnel breaks, media, ...) > Display changes in databases	> Duplicate entries > communication errors among teams (missing information or varaltet) > Zerostatus (antibody) there is this field > Hotline can do a lot but are not aware of responsibilities
5.Which process step do you see as difficult or complex?	The transition in Sormas could be problematic.	Technology	> The complete front work (case investigator)	Whole case investigation, as different teams work on one case.
6.Where is outside (external) help needed?	> Database customization - help from (forms) Access experts are needed here.	Senate administration (test center coordination) Hospitals, other districts	> Medical facilities, schools, employers must provide input	Hospitals, schools
7.how many IT systems do you have to operate?	> Standard systems such as Word, email system > Access (database), Demis (reporting software), Survnet (state laboratory reporting software to RKI),	Survnet, COVID-19 database, Sormas, standard systems	ACCESS, Survnet, Standard Systems, personally no work	Survnet, COVID-19 database, Sormas, standard systems, demism message

8.how often is information missing during the process? Is it important information? What is the impact of the lack?	No	Telephone numbers are often not given; therefore a lot of research is required The slips of paper to fill in -- often not legible	> daily, acute gaps but not serious.	Addresses or telephone numbers of citizens are not provided by the laboratory. Often, this information is also lost in the process. This requires a lot of reworks.
9.How often does organizational change occur?	Switch to sormas (big organizational change , they had many problems; RKI loses monopoly of Survnet due to Sormas) LUKA app --- just no message from LUKA	Armed forces, districts, schools, hospitals -- very often.	> Personnel change/transfer	Often, because many teams are working together, but it is now much better than before. The only problem is that with the change, new information is only passed on and not old but still valid information.
10.How often do loops occur between the participants?		>Berlin and Brandenburg - Responsibilities >Schools also want to identify contacts	> Very rarely > Very clearly defined responsibilities	In the case of responsibilities of citizens, loops are formed, because mother has a different processor than father and this can actually be processed directly as a family. In addition, the Hotlein can also answer directly but then always pushes the requests to the investigators.

11.How often do you need to change the media? (is it all digital?)	In person, not often. But a lot still goes by fax.	Checklists for telephone call, PC, …	Laptop, paper, fax, telephone, copier/scanner,	
12.Can you describe special cases?		An entire apartment block has become infected (Pentecostal church), conspicuous only after too many reports.	Erroneous addresses, adaptations to new regulations	
13.Do you see any redundancies (for example duplicate testing)?	Duplicate entries in the databases	In case processing, citizen contact, multiple agents on one family	Duplicate entries, cases that are created twice, two caseworkers process the same case/consultation,	Families are served by different staff because of different names or multiple calls. Cases are duplicated due to misspelling or from contact person to positive person.
14.Can you identify at least one or more bottlenecks in the process?		In case administration and hotllein must be processed quickly.	> Mobile working, very cramped workplace > Little workplace and technical equipment > Qualified personnel	
15. Which activities take a lot of time? What are the waiting times? Is the lead time too high?	Duplicate work	No waiting times	There is tracking for times, so usually nothing gets left behind.	

16.Where do you see potential for improvement?	Political entities (politicians, RKI, ...) hinder the progress of Sormas, since Sormas could also be used in many ways later, e.g., for water systems ... Behavioral uncertainties are there,	In digitization, but in the process itself, it is quite well positioned.	The potential lies in professionalism, technical skills and contact with citizens. Decongestion of jobs through mobilization. Performant infrastructures and stronger interdiciplinary recommendations and not only RKI.	Uniform case work so that a person can only be created once.