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TARGET OPERATING MODEL FOR PROCESS MINING

Lappeenranta–Lahti University of Technology LUT

Global Management of Innovation and Technology Master's Thesis

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ABSTRACT

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Process Mining is a relatively new discipline that connects data and process sciences. It combines data mining techniques and process improvement approaches to enable organizations to discover, validate and enhance their processes thus, creating business value by uncovering value in their data.

The thesis studies process mining and investigate existing applications to understand process mining capabilities and industry best practices to implement process mining. The thesis aims to identify how a company can initiate process mining and scale it on enterprise-level and what elements are needed to operate it successfully.

The study first generated a framework to illustrate what is needed to start and scale process mining initiatives in an organization. It also generated a target operating model that different organizations can adopt. The study suggests that for process mining implementation, the organizations need to define a clear organisational structure and a governance model; well-documented processes, controls, and capabilities; well-designed technology landscape; data management; sourcing principles and processes; and how to empower people and support continuous improvement change culture. As a result, it produces a target operating model that includes how demand development and monitoring can be operated to enable continuous improvement and innovations.

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
AVATAR	Adversarial System Variant Approximation
BI	Business Intelligence
BPM	Business Process Management
BPMN	Business Process Model and Notation
CoE	Centre Of Excellence
CRM	Customer Relationship Management
DIKW	Data Information Knowledge Wisdom
DM	Data management
DAMA	Data Management International Foundation
DMO	Data Management Office
ERP	Enterprise Resourcing Planner
IT	Information Technology
IEEE	Institute of Electrical and Electronics Engineers
GDPR	General Data Protection Regulations
KPI	Key Performance Indicator
ML	Machine Learning
SAFe	Scaled Agile Framework
RDS	Responsible Data Sciences
RPA	Robotic Process Automation

1 INTRODUCTION

There have been many discussions about the value of data in recent years, and “data is new oil” has become a common refrain. (Bhageshpur, 2019). As the phrase hints, data is becoming the fuel of new developments, value creations and growth of organisations (Deloitte, 2020) while noting that data is an only raw material for information and knowledge. (Ross, 2016). To benefit from the “oil”, the companies need a way to discover and realise their data's potential and how to use the data. (Deloitte, 2020) As British mathematician Clive Humby stated, “Data is the new oil. It is valuable, but if unrefined, it cannot really be used. It has to be changed into gas, plastic, chemicals, etc., to create a valuable entity that drives profitable activity; so must data be broken down, analyzed for it to have value” (James, 2019, p.23).

Industrial companies have collected significant data in their information systems during their regular business activities such as sales, marketing, and customer services. In 2019, Splunk Inc published a report based on a global survey conducted with over 1300 business managers in 7 countries. Despite discussing the value of the data, according to the report, %55 of the organisation data is unknown, or the organisations do not know how to find and use the data. (Splunk, 2019). Many referred to the unknown and untapped data as dark data, which is defined as “the information assets organisations collect, process and store during regular business activities, but generally fail to use for other purposes (for example, analytics, business relationships and direct monetising).” (Gartner Information Technology Glossary).

The emergence of data sciences in many organisations and academia indicates a growing recognition of dark data and information as an asset. The organisations are discussing utilising data and turning it into a business asset. Gartner predicted that 10% of organisations would profit by productising and commercialising their information asset. (Gartner, 2017). Despite recognising dark data and information assets as big steps forward, new challenges appeared in understanding and using data for different purposes.

Existing research mainly focuses on the technical aspects of data, data mining, and process mining. Yet, there are a limited number of research to help organisations be operationally ready to benefit from the data, data sciences. Therefore, this research aims to study the transformation of event data that organisations collect, process and store during regular business activities and which can be turned into information and knowledge of processes to be utilized as a business asset with the implementation of process mining.

1.1 Background

Traditionally, process modelling is on assumed processes, not on actual processes and their execution. (Jouck et al., 2018) Process improvements are also mainly ruled by what is said or observed, not what is done during the processes. (Rubin et al., 2007) Modelling and improving the processes based on observations or assumptions may not be easy and may not provide correct results. For example, an Enterprise Resourcing Planner (ERP) has many complex workflows, and many individuals are working on the same stage of the workflow or following each other's actions. (Van Der Aalst, 2016)

In addition to complexity, other challenges such as management commitment, end-user communication and involvement are recognized. The management might already have an idea of how the process should be or how it should be improved; this may lead to a lack of systematic analysis, studying and collaborating with end-users, and identifying weaknesses and bottlenecks. (Parkes, 2002) Also, in many cases, the quality of business process analysis, design, improvements rely on human factors, which may concern cognitive biases. For example, completeness and testimony biases may influence incomplete process model issues (Razavian, Turetken, and Vanderfeesten, 2016)

It is challenging to observe a system manually to discover the as-is process and identify the bottlenecks and improvements using process developments methods without utilising the data considering aspects explained above. Also, it is hard to overcome the challenge with existing data mining tools alone in a satisfactory manner as data sciences tend to be process-agnostic. On the other hand, process mining is both data-driven and model-driven. It can link process and data sciences with extracting knowledge from event logs to discover, monitor, and improve processes. (Van Der Aalst, 2016)

1.2 Objective and Limitations

The research aims to design a target operating model that different companies can adopt in various industries to plan and execute process mining projects and services in a repeatable and actionable manner. The research studies different types of process mining to understand the application's capability, various examples in several industries where and how the process mining is applied to analyse expected and actual outcomes. As an output of the study, a target operating model will be produced to help the organisations deliver value through process mining by studying best practices executed by companies so far.

As process mining is a new discipline, publications and shared best practices are limited. There are not many people who have sufficient knowledge in the industry. Additionally, some process mining capabilities are still executed only as proof of concept, and the use cases shared by the companies and service providers are initiatives where the project or program was executed successfully. Therefore, the research is limited to rely on success stories; there is insufficient data related to failed process mining initiatives other than a few surveys conducted by the research companies.

1.3 Research questions and objectives

The study aims to help public and private organizations such as corporates, companies, public services identify how they can deliver value through process mining; start, implement, and deliver results continuously. Moreover, if possible, the research will draft an operating model for the organisations that can provide value and how the organisations run. Therefore, the research question is formularized as:

Research question: What would work as a target operating model for process mining that different companies can adopt?

In order to draft an operating model, the study first tries to answer why organisations use process mining and the value it can bring. Therefore, a sub-research question is formalized as:

Sub-Research question 1: What value can mining bring to organisations?

Then the research raised a second sub-research question to understand how organisations implement process mining projects and services, organisation structures and governance model; what kind of processes and measures are used; what are the needed people, skills, and technologies.

Sub-Research question 2: What are the best practices and lessons learnt established so far in different industries and sectors?

The second question is divided into sub-focus areas to understand the implementation of process mining from different aspects.

1. What was the goal and vision of the companies? What did they want to achieve?
2. What kind of capabilities did process mining offer, and how did it meet their expectations?
3. How did the companies manage the data?
4. What kind of organization, people and expertise did they need?
5. Which software and technological landscape did they use?
6. What were their Organisational Structure and Governance Model?
7. How did they measure the change?

1.4 Execution of the research

The study's execution consists of three leading phases. The first phase includes literature reviews to understand process mining and its different types. The second phase is divided into iterations executed throughout the entire phase two. Each iteration included reviewing the latest publications in academia, research of companies, and use cases published by companies. The purpose of executing the phase in iteration was to be agile during phase two to gain knowledge continuously from fast-developing fields by using the latest data, trends, and findings. The third and final phase focus on generating an operating model based on the findings.

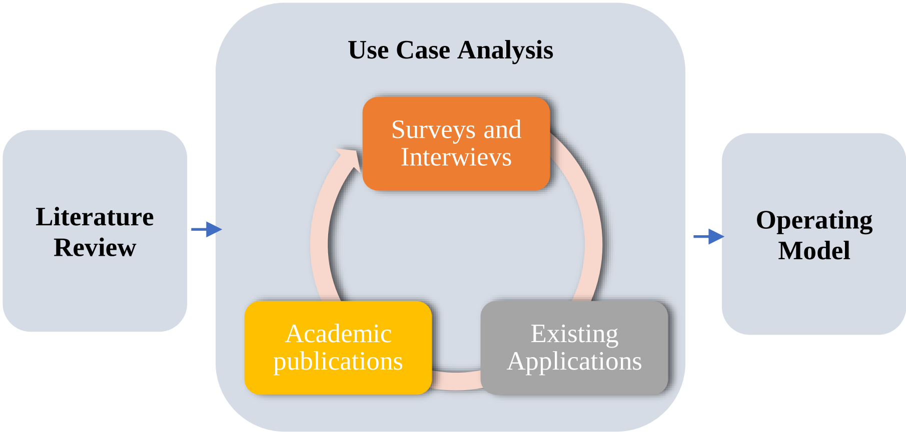

Figure 1 Execution of the Study

1.5 Structure of the Thesis

The thesis consists of seven main chapters where data and knowledge from different execution phases are visible.

The introduction is the first chapter where the background information, motivation of purpose of the research is given with execution and structure details.

Key concepts, literature review are reflected in chapter two and partially in chapter four. Process Mining, its type, different capabilities are covered in these chapters.

The methodology is explained in chapter three, which includes selecting databases, research consisting of surveys, interviews, and use cases.

Application Analysis is started by collecting and analysing the HSPI Process Mining application database and other studies to map the applications through different industries and sectors and understand the adoption of process mining. In chapters four and five, different uses cases are analyzed. Chapter four identifies process mining capabilities and adaption for different use cases. Chapter five focuses on implementing; how the different organisations started to use process mining, their data management, resources, technologies used, organisations and governance models and performance indicators, monitoring and continuous improvement activities.

A draft of the operating model, as a result, is shared in chapter six, followed by **discussions and a conclusion** in chapter seven.

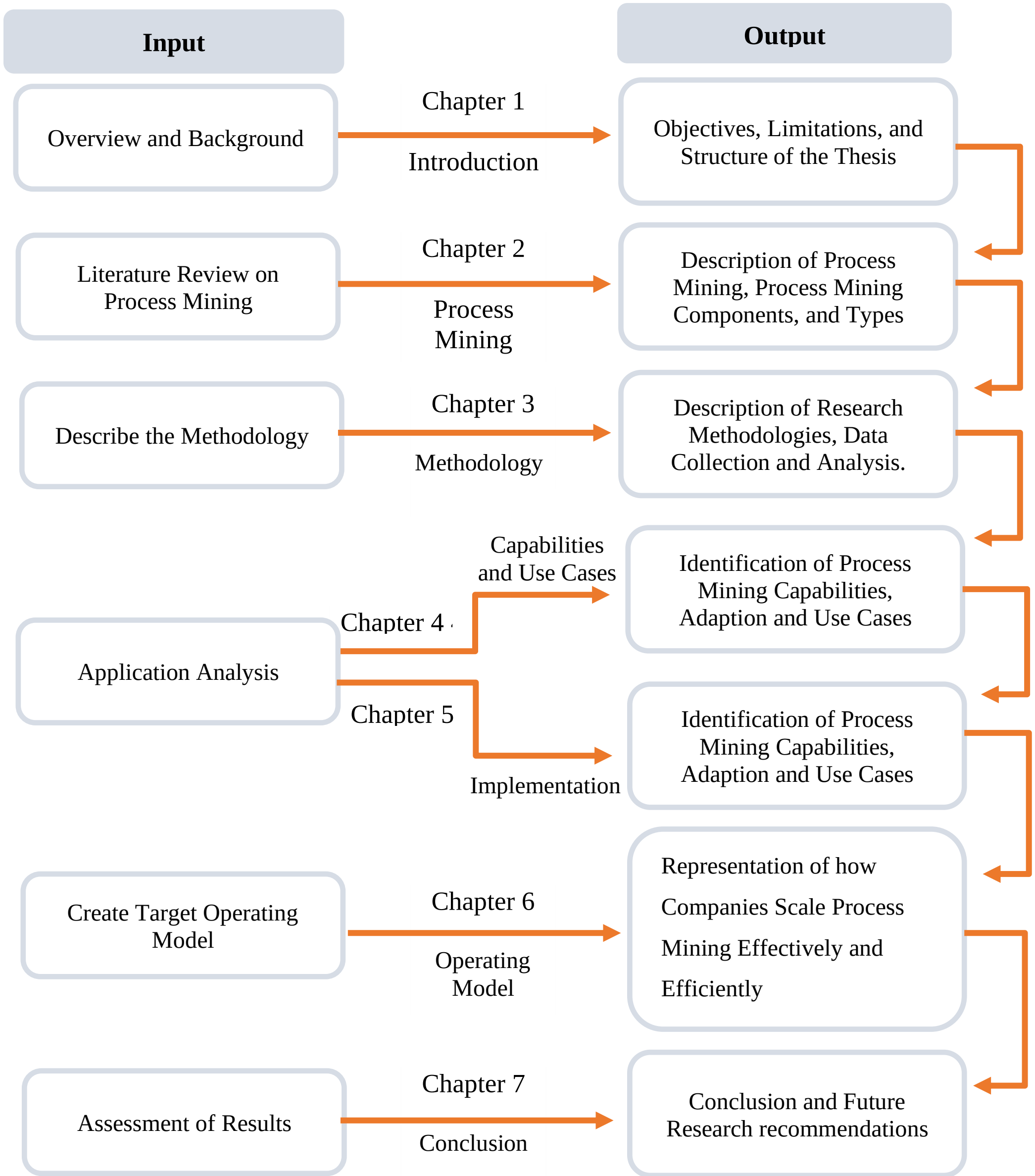

Figure 2 The Structure of the Thesis

2 PROCESS MINING

Process Mining is a relatively new discipline. Research focusing on process mining increased only in the late 2000s after establishing the Institute of Electrical and Electronics Engineers (IEEE) task force (2009) and publishing process mining manifesto (2011), while few papers discussed process mining problems (i.e., Cook et al., 1995). The first book related to the discipline, "Process Mining, Data Sciences in Action," was published in 2016 by Will Van Der Aalst. Still, the book is used as a primary reference in many publications.

The Process mining manifesto explains process mining as "a discipline that sits between computational intelligence and data mining, on one hand, process modelling and analysis on the other hand". (Process Mining Manifesto, 2012) Process mining combines model-based process analysis and data-centric analytic techniques to discover processes and seek a confrontation between data and process models. Process mining aims to extract insights from data gathered from information systems to discover the processes, generate ideas for process improvement, and compare the as-is process with the modelled process. In brief, process mining aims to use data and actionable insights gained from data to create value. (Van Der Aalst, 2011)

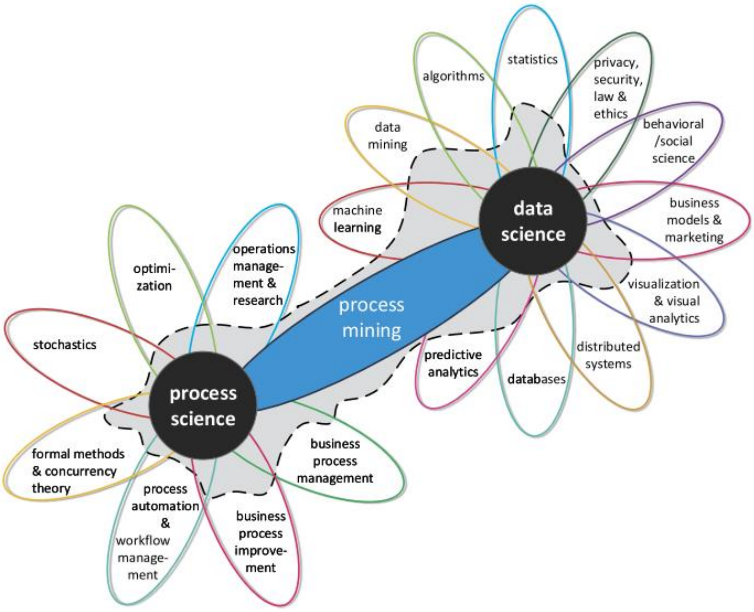

Figure 3 Process Mining as a Bridge Between Data Sciences and Process Sciences. (Source: Van Der Aalst, 2016)

Process Mining starts with extracting insights from data and using the information, knowledge, and wisdom gained from data to discover, diagnose, and enhance process models. Therefore, this chapter first focuses on knowledge management to understand data enrichment and value realization in process mining. It studies components of process mining to understand what is needed for process mining and different process mining types: process discovery, conformance checking and enhancement to understand the capabilities of process mining.

2.1 Data Enrichment and Value Realization in Process Mining

DIKW (Data Information Knowledge Wisdom) is a model known for applying information processing concepts. It helps companies extract information from data, facilitate knowledge and apply wisdom. (Conger and Probst, 2014) To understand the data to value cycle in process mining, the research will use the DIKW pyramid to illustrate data, information, knowledge, and wisdom and how data is transformed into information, knowledge and how the transformation creates an opportunity for value creation and realisation.

Data is characterised “as being discrete, objective facts or observations, which are unorganised and unprocessed and therefore have no meaning or value because of lack of context and interpretation.” (Rowley, 2007) In process mining, we can consider event logs as data in the first level of the DIKW Pyramid.

Information is described as “organised or structured data, which has been processed in such a way that the information now has relevance for a specific purpose or context, and is therefore meaningful, valuable, useful and relevant.” (Rowley, 2007). In the context of process mining, information could be considered as discovered process model as the data is processed and provides details about the process.

Definition of knowledge is “synthesis of multiple sources of information over time, and the organisation and processing to convey understanding” while wisdom is defined as “the ability to increase effectiveness. Wisdom adds value, which requires the mental function that we call judgment” (Rowley and Hartley 2017). In the context of process mining, knowledge and wisdom come after conformance checking, and enhancement as those provides details related to where, when, and why errors occur and how we can improve.

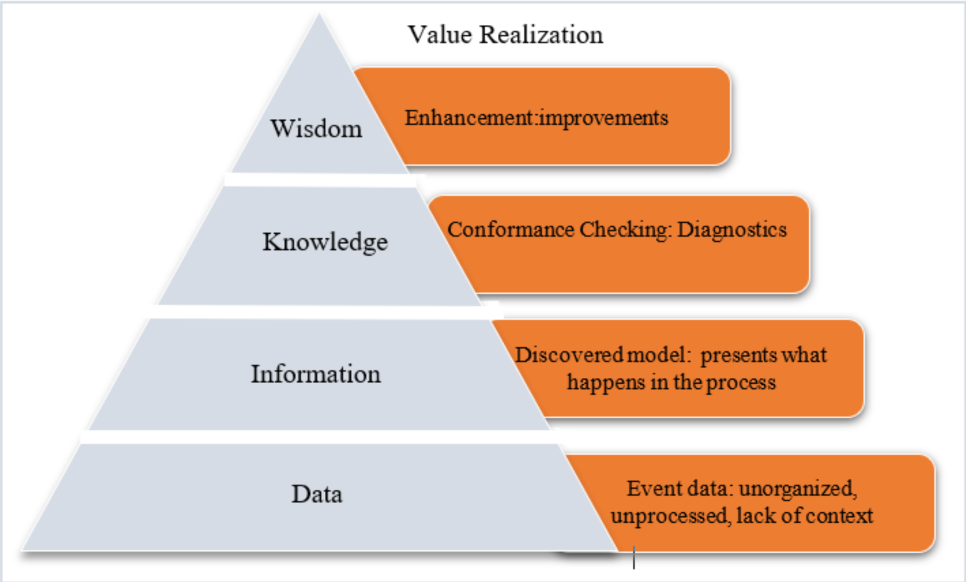

Figure 4 DIKW and Value Realization 8 (Adapted from Soloviev K., 2016)

2.2 Components: Event Logs and Process Models

The primary components are event logs and process models in process mining. Event logs of any information system are recorded based on the background's real process if the models are rich enough to generate even data. Process models are either given to simulate the behaviour or generated by given event logs. (Van Der Aalst, 2018) There are three ways to establish a relationship between process models and the behaviours (based on event logs): play-in, play-out and replay.

Play-in, also referred to as inference, uses example behaviours (event logs) as input and construct a model as an output. Automated Process discovery is one example of the play-in. (Van Der Aalst, 2016). The automated process discovery is a widely investigated operation; Its methods take event logs as input and produce a business process model based on control flow relation between observed tasks in the event logs. (Augusto et al., 2018)

Play-out is the opposite of play-in. It uses a process model as an input and generates possible behaviours. The play-out is mainly used to simulate the process to analyse and enact. (Van Der Aalst, 2018).

On the other hand, Replay uses both event logs and process models. It targets establishing a relationship between the events and the model by displaying the logs on the model. It is possible to identify the bottlenecks, diagnose the deviations, and help construct predictive models. (Van Der Aalst, Adriansyah, and Van Dongen, 2012)

2.2.1 Business Process and Process Models

The Cambridge dictionary defines a process as “serious of actions that you take to achieve a result.” (Cambridge, 2020) The business process is defined similarly in many resources, a sequence of activities implemented or executed in the sequence of occurrence. The processes are expected to influence the cost, time, and quality in a business environment. The process models illustrate and document the process; in other words, they are a graphical representation of the processes. (Lana Glossary, 2021)

Process mining can generate process models, compare the as-is models with the target models and provide insights to enhance if needed. Therefore, process mining is highly concerned about the process model that is also one of the differences between process mining and data mining. (Van Der Aalst, 2016)

2.2.2 Event Logs

A significant amount of data is collected and stored in software and hardware systems; activities on mobile devices; app data, log in to web pages, smart TVs, intelligent robots, intelligent elevators (elevator calls, maintenance information). Each action of a user or machine can be recorded as an event. (Leemans, Fahland and Van Der Aalst, 2018)

The events contain details to identify various information such as what was done, when, by whom. The event data is available in many information systems such as Customer Relationship Management (CRM), Enterprise Resource Planning (ERP), or Business Process Management (BPM) systems. (Tax, Sidorova, and Van Der Aalst, 2019). An event log is generated based on a process consisting of cases. A case consists of events and may have multiple attributes such as activities, timestamp, cost, resources. (Van Der Aalst, 2016). Fluxicon suggests Case ID, Activity and Timestamp as a minimum mandatory requirement for an event log. (Fluxion Process Mining Book, 2020).

Using the IT Incident Management system as an example, we can consider incident management as a process (starting with a customer reporting an incident, ending with closing the incident). In this case, each issue reported can be a case. The cases can have multiple activities; Incident Logging, Response, Resolution. (The activities are inspired by The DevOps incident management process (Atlassian, 2021). The event log for the process may include the data in the table below.

Table 1: Example Event Logs

Case ID	Activity	Start TimeStamp	Complete TimeStamp
Incident 1	Incident logged in	03.02.03, 15:15	03.02.2021, 15:20
	Response	03.02.2021, 17:20	03.02.2021, 17:20
	Resolution	03.02.2021, 19:20	03.02.2021, 21:20
Incident 2	Incident logged in	03.02.03, 15:20	03.02.2021, 15:25
	Response	04.02.2021, 15:00	04.02.2021, 15:00
	Response	06.02.2021, 15:00	06.02.2021, 15:00
	Resolution	07.02.2021, 15:00	08.02.2021, 15:00

If the above event log is used to discover the process model(play-in), it can construct the model below. (Note: this example is used the demonstrate. It is not taken from real examples, and it is kept simple.)

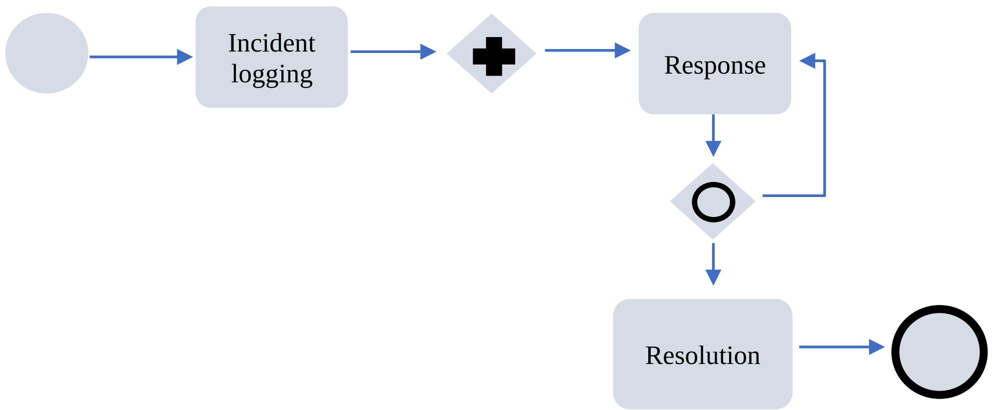

Figure 5 Process Model Example 1 (using the Business Process Model and Notation (BPMN) notation)

If the below model were given, it would not be able to generate an event log as in Table 1 as there is no possibility to replay the activities of incident 2.

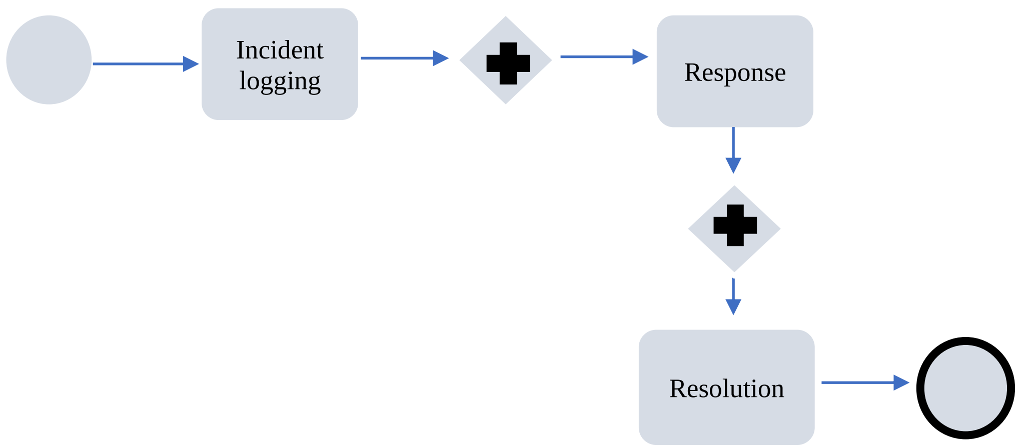

Figure 6 Process Model Example 2 (using the BPMN notation)

The event log must have enough correct data to generate a model or be used in the replay. Several challenges are identified while working with event logs, and they need to be handled by the algorithms used for proper process discovery, conformance checking and enhancement.

1. The event Logs may have an unexpected absence or presence of behaviours. They are considered as **noise**. (Buijs, 2014). The noise could result from data quality issues such as logging errors. Some algorithms claim to be noise-tolerant capabilities, but they may drop 45% accuracy when the noise level is 3% of the total log size. (Conforti, La Rosa and Hofstede, 2015)
2. **Infrequent** behaviour may be the exceptional behaviours or behaviours that occur less frequently than normal behaviours. (i.e. there might be a model to follow for each event, but in case an unexpected (or complex) problem occurs, an ad-hoc solution could be provided out of the scope of the model). This type of behaviour could be included in the analysis depending on the goal. (Leemans, Fahland, and Van der Aalst, 2018)
3. Event logs may not contain enough information; they can be **incomplete**. There could be various root causes for the incompleteness, while one of the most common is the high number of parallel behaviour activities. A model produced based on an incomplete event log may present behaviours that do not exist in the actual process

or exclude some of the actual model's behaviours. (Tapia-Flores, Rodríguez-Pérez, and López-Mellado, 2016.)

2.3 Process Discovery

Process discovery is a method or type of process mining that takes as input event log and produces an output a representative process model. (Augusto et al., 2018) Discovering what is happening in the actual process based on historical event data can help identify bottlenecks, eliminate non-value-added activities, reduce waste, and visualise unnecessary waiting rework to improve resource management. Discovering the model is a starting point of analysis; it answers "what happened?". When the events are related to the discovered model, other analyses such as checking conformance, performance analysis, identifying bottlenecks, eliminating non-value-added activities, reducing waste, resource allocation, predictions and recommendations can be completed. (Van Der Aalst, 2016)

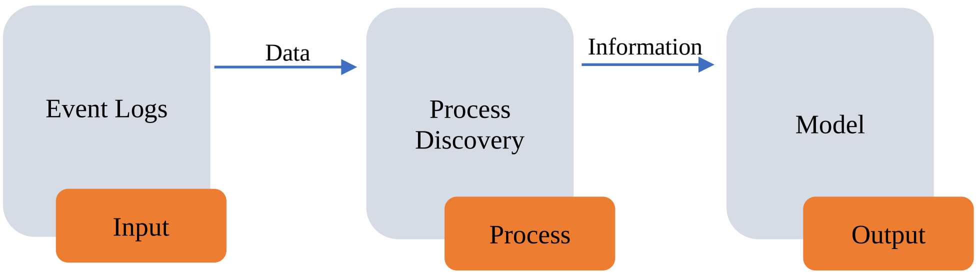

Figure 7 Process Discovery

The model should represent the behaviour seen in the given event log. There are four quality criteria to operationalise the representation. (Van Der Aalst, 2016)

1. Fitness is related to being able to replay all event log on the model. For example, for the event log given in table 1, the process model example 1 (Figure 6) has perfect fitness. However, incident two cannot be displayed in example 1.
2. Precision is related to underfitting; a flawed precise model allows behaviour, not in the event log.

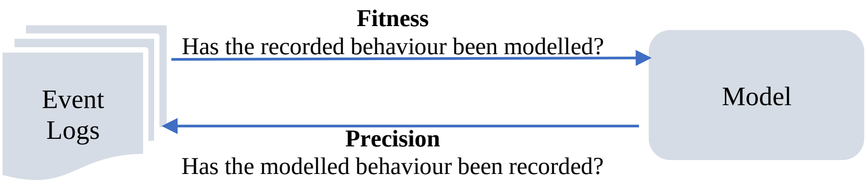

Figure 8 Process Discovery, Fitness and Precision.(Adapted from Carmona, J., van Dongen, B., Solti, A. and Weidlich, M., 2018)

3. Generalisation is related to overfitting; process models are expected to generalise the behaviour recorded event logs.
4. Simplicity refers to Occam's Razor principle. It is related to the process model being the most straightforward explanation of the underlying process.

The balance of four dimensions, fitness, precision, generalisation and simplicity, depends on use cases. For instance, audit-related use cases may require a high fitness model; optimisation related cases may require a high precision model, or they might not be a model that scores well on all criteria. (Buijs, Van Dongen, and Van Der Aalst, 2012) The process discovery algorithms must balance the four dimensions based on the use cases and the analysis objective.(Leemans, Fahland, and Van Der Aalst, 2018) Later in 2019, Jans and Depaire discussed a new quality perspective for process discovery to cast new light on the quality dimensions and metrics. They discussed that the quality of a model could have different interpretations, fitness and precision metrics could be biased estimators between the resemblance between the model and the underlying system, and generalisation cannot grasp the relation between the model and the system. (Janssenswillen and Depaire, 2019). Recent research studied if deep learning-based methodology, Adversarial System Variant Approximation (AVATAR), could be used to overcome quality measurement-related issues, especially generalisation. (Theis and Darabi, 2020) The paper anticipated further researchers focusing on more advanced log fitness and precision methods for precise and absolute generalisation measurements.

One desirable process discovery property is re-discoverability; the original process should be rediscoverable by the discovered process. (Leemans, Fahland and Van Der Aalst, 2013). A model may be rediscovered when the event log's quality dimension (noise, incompleteness, infrequent behaviour) and the process discovery's quality dimension are on a satisfactory level only.

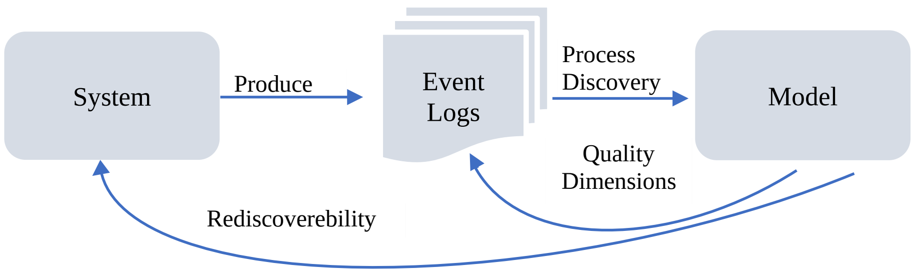

Figure 9 Model Quality, Rediscoveribility (Adapted from: Tapia-Flores, T., Rodríguez-Pérez, E. and López-Mellado, E., 2016)

2.4 Conformance Checking

Conformance checking is defined as "the analysis of the relation between the intended behaviour of a process as described in a process model and event logs that have been recorded during the execution of the process." (Carmona et al., 2018). As seen in figure 10 below, the event logs and model (constructed by people or discovered from event logs) are inputs, and the output is diagnostics (nodes where the given model and the logs are not aligned).

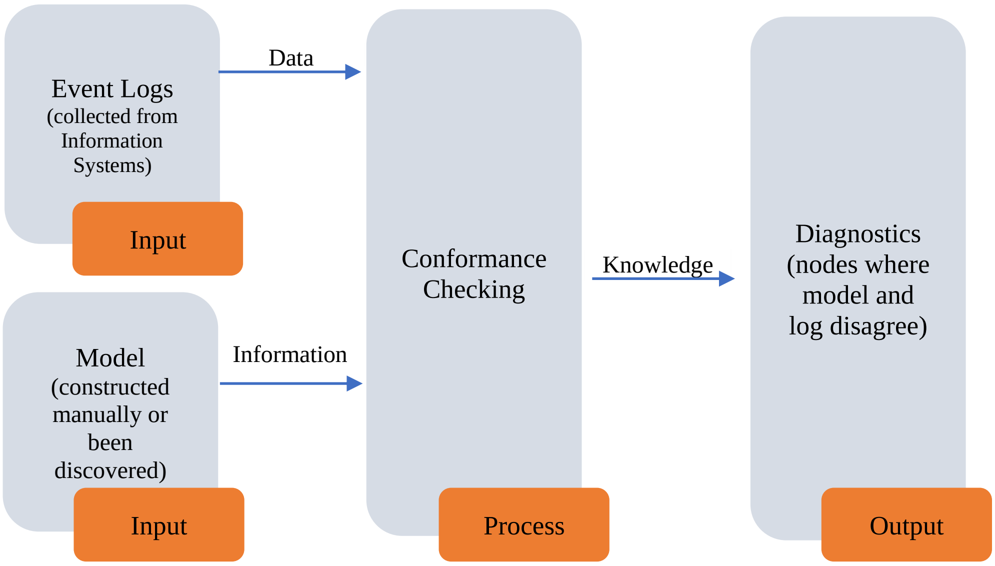

Figure 10 Conformance Checking

In summary, the goal is to identify commonalities and the differences between modelled and observed behaviours.) (Van Der Aalst, 2016). The goal can be achieved by either log-model conformance checking or model-model conformance checking. Log-model conformance checking assumes that the event logs represent the reality, while model-model conformance checking assumes a given model (could be referred to as system process) represents the reality. (Leemans, Fahland and Van Der Aalst, 2013)

Conformance checking is devoted to computing the relationship between actual and discovered processes. There is two mainstream conformance checking results. (Carmona et al., 2018)

1. The actual and observed processes are aligned; in this case, the results can be considered evidence of the model's validity, compliance assurance of the recorded trace, and the model's use to provide predictions such as time and cost.
2. There is a deviation between the real and the observed processes. The deviation may occur as mild problems caused by lack of coordination and communication, wrong recording activities. However, it could also be a severe problem caused by corruption in data or decision-making against its code of conduct. The deviation can also bring new insights for the companies; an employee may be managing the work more efficiently, improving the process model.

Conformance checking methods should support two viewpoints. The first is to consider that the given model may not reflect reality and needs to be corrected or improved. The second one is to consider that the cases deviate from the model, and a better control mechanism to enforce better conformance needs to be developed. (Van Der Aalst, 2013) For instance, systems can be configured to prevent unexpected behaviours.

2.5 Enhancement

Process enhancement is process mining that focuses on enhancing processes using event logs and process models as input. The enhancement aims to repair, extend or improve the existing process models and produce new models. (Van Der Aalst, 2016).

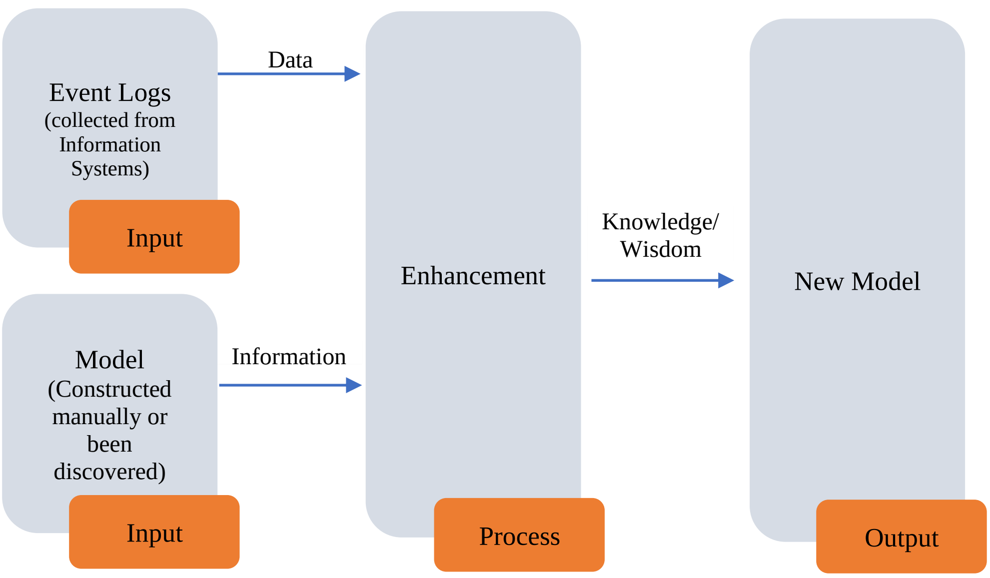

Figure 11 Enhancement

Recent researches discuss two types of enhancement considering multiple perspectives. Repair as one type considering control-flow perspective and Extension as another type considering organisation, time and case perspectives. (Yasmin, Bukhsh and Silva, 2018)

Repair targets repairing the model if the model does not fully reflect reality. (Van Der Aalst, 2016). Improving conformance checking diagnosis is one of the use cases for model repair as conformance checking identifies differences between modelled and observed behaviours. Diagnosis of conformance checking can be used to repair the model; for example, if a path that is not being used could be removed or additional conditions and paths can be added if they exist in reality to reflect reality better. The repair can be used to support monitoring process evaluations and supporting customisations. (Fahland and Van Der Aalst, 2016) Many papers (e.g. Fahland and Van Der Aalst, 2016, Polyvyanyy et al., 2016) have used fitness as the main criteria for repairing and precision, generalisation and simplicity as secondary criteria. However, this seems to be an accepted approach considering that precision, generalisation and simplicity can be considered if the fitness is acceptable. (Buijs, Van Dongen and Van Der Aalst, 2012)

Extension, the second type of enhancement, aims to add a new perspective by extending the model by adding new data such as time, resources, decision rules. For example, adding data related to resources can be used to analyse working patterns; adding data related to time helps identify bottlenecks, measure service levels, and predict processing times; adding case-related data helps with decision-making trees. (Van Der Aalst, 2016).

2.5.1 Organisational Mining

Organisational mining focuses on the organisational perspective to explain behaviour observed by constructing a business process model. (Van Der Aalst et al., 2007) Organisational mining can be divided into four categories. (Zhao and Zhao, 2014)

1. Organisational structure discovery aims to obtain the current business process.
2. Social network analysis aims to identify a relationship between resources and activities to explore the bottlenecks and improve the process.

3. Resource allocation aims to improve resource allocation and predict resource requirements.
4. Role mining aims to identify the roles.

2.5.2 Time and Probabilities

The time perspective adds the timing and frequency information by adding timestamps to event logs. (Van Der Aalst, 2016). The timestamp record the time of occurrence of an event, and this data can help identify lead time, wait time, service time and utilisation of resources. (Van Der Aalst et al.,2007). The time attributes can also support the prediction of the next event time, remaining time, activity delays. (Mehdiyev and Fettke, 2020.)

2.5.3 Decision Mining

Case perspective helps to analyse choices and decisions made in the process. Decision mining focus on understanding decision points, and data influence the decision. (Rozinat and Van der Aalst, 2006) Decision mining provides decision tree learning, and It can analyse alternative response variables with additional predictor variables such as behavioural information and time information. In some cases, contextual such as environment, workload data can also be used. (Van Der Aalst, 2016). For example number of cases, an employee is working in a day can influence the decision, or having four working days in a week may improve the efficiency.

3 METHODOLOGY

This study analyzes existing surveys, interviews, published use cases, and other publications to identify why organizations used process mining and how they use it. And it aims to provide an operational model to guide companies considering trying process mining and share lessons learnt among existing practitioners. This chapter describes the research process and design, including data, literature, case gathering and analysis, and reliability and validity assessment.

3.1 Research Approach

Goddard W. and Melville S. indicate that good research is planned, organized and has a specific goal. (Goddard and Melville, 2004) In that spirit, the author planned and structured the research for a specific goal while identifying the right approach, data and literature source and analysis.

As Process Mining is a relatively new discipline, few books are published, and the maturity of knowledge is low in many companies. That said, leading research companies run interviews, surveys, and research to define market guides and answer common questions, while the number of publications is increasing significantly. Considering these facts, the author decided to conduct the research by reading widely in the field, comparing and analyzing different points of view, and developing new insights.

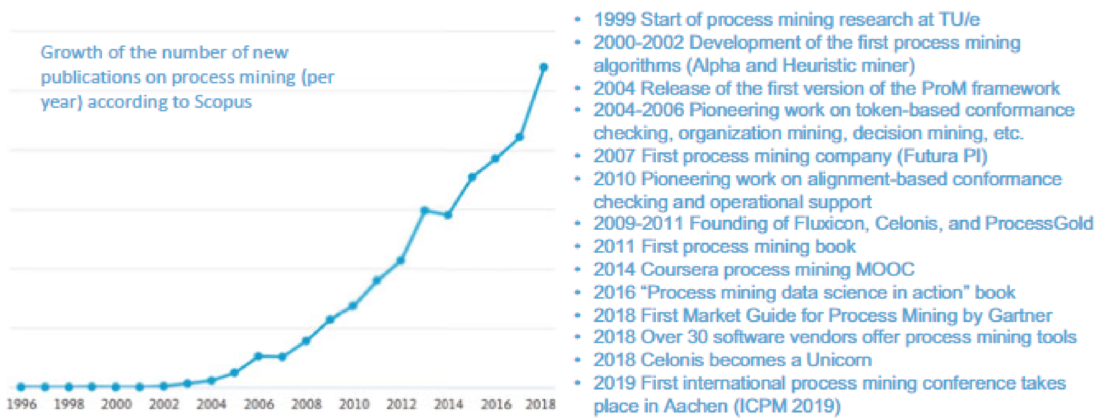

Figure 12 Growth of the Number of Publications on Process Mining. (Source: Process Mining in Action. Reinkemeyer, 2020)

The research studies to understand what value process mining bring to companies, how it is implemented, and the study targets to return a target operating model as a result. However, considering the nature of operating models, there cannot be one final model that works for every company; the companies need to design and develop based on their operating principles and adapt to the continuously developing technology environment. Considering these reasons, the author designed the research as exploratory, as the purpose of exploratory research can generate insights and does not necessarily recommend the final solution. (Chawla and Sodhi, 2011)

3.2 Data Collection and analysis

While designing the research, the need to have a more in-depth understanding of process mining, interrogating different understandings, and enhancing validity are realised. Therefore, the author selected the triangulation technique to collect and analyse as the technique supports the need based on the definition by Nightingale. (Nightingale, 2020) The author used the secondary data collection method and two qualitative data collection methods for insights.

1. Document Analysis: The research started with two main resources of process mining books, “Process Mining: Data sciences in action” By Van der Aalst (2016) and Process Mining Manifesto. The book is selected as it is the first book about process mining, and many papers use it as the primary reference. Based on the knowledge gained in these books, the author also identified connected papers published related to multiple sub-topics of process mining to baseline the theory by using search terms.

   “Process Discovery”, “Conformance Checking”, “Process Enhancement”, “Bottleneck in a Process”, “Process gap analysis”, “Auditing a Process”, “Process Improvement”.

2. Analyzing the applications and use cases: The research analyses the HSPI Process Mining application Database that includes all the historical information about process mining applications. (Cotroneo et al., 2021). The analysis of the database

help to gain insights on process mining applications and validate information shared by different parties.

   a. While analysing process mining applications, the author also used secondary data, “Process Mining in Action” book by Reinkemeyer (2020), and customer references shared different service providers to analyse case studies.
   b. Interviews and podcasts conducted by different parties are analyzed to gain more insights and validate information shared by various resources.

3. Analysis and observations based on market research: The author used market research and surveys of leading research companies such as Gartner and Deloitte. The author also analyzed offers of service providers to understand capabilities, direction, challenges and compared the offers with the application database to see what currently process mining software companies are offering and how realistic the offer are.
   a. Gartner surveyed process mining vendors and shared their findings related to process mining adoption, use cases, and the focus of different vendors. The author used Gartner survey results as secondary data to understand process mining capabilities and use cases. The analysis was used to select example use cases to study. (Gartner Process Mining Market Guide. Source: Kerremans et al., 2020)
   b. Deloitte surveyed process mining practitioners intending to understand how organizations adopt process mining, assess benefits, and identify success factors. The survey was used as secondary data to gain insights on expectations and success factors. (Deloitte Process Mining Survey. Source: Galic and Wolf, 2021)

According to Renner, M. and Taylor-Powell, the qualitative research process depends on the questions, the need and the resources and requires creativity, discipline, and a systemic approach. They suggested a three-step approach to analyse data used in this research: familiarizing with data, identifying and focusing on questions, and categorising the information. (Renner. and Taylor-Powell, 2003)

As the first step, the author reviews books, the manifesto, and the connected papers to have a theoretical base in process mining. In order to generate an operating model, the author focus on understanding what process mining offer, what value the organizations gain so far and how they gain. Furthermore, a group of codes was developed and used to analyse the application database based on knowledge gained.

Table 2 Design of Codes Used for Qualitative Method Part One.

Question	Elements to be coded	Codes
1. What are the industries and sectors?	Application of process mining in different sectors and industries	Sector Industry
2. What type of process Mining is applied?	Applied process Mining types	Discovery Conformance Enhancement Detect Predict Recommend
3. What were the Use Cases?	Use cases of process Mining	Discovery Improvement Bottlenecks Conformance Data Digital Transformation Automation Auditing, Compliance Operations
4. Do offers related to process mining are realistic?	Expectation Management	Offers Expectation Goal Result

Question number one could be answered based on the data provided in HSPI application Database as “industry” and “sector” data was given per application. Figure 18 is generated, which provides insight on applications of process mining in different industries and sectors.

Then the question two and three were raised. The codes were designed based on Gartner’s market research and the document review as it was challenging to align the terminology used in academic publications alone and HSPI Database. Based on the findings, the author has chosen four case examples of different vendors based on the factors below:

1. The most common process is which process mining has applied to so far (process improvement in cash-to-order). The process is identified based on analysis of the HSPI Process Mining applications Database
2. The increasing trend in technology: Digital Transformation and Automation. The trends are selected as suggested in Gartner's process mining market guide.
3. Experience. ABB case is selected as the company is one of the companies that has been using process mining for over a decade globally.

Analyzing different use cases also provide insights into what software vendors offer. At this stage, the author compares this information with Deloitte's survey to align with practitioners' expectations. The author also analysed the interviews, podcasts, testimonials, and videos shared. Finally, the author compared the offer and expectations with the data provided in the HSPI Database and case examples shared in the book by Reinmeyer (2020) and other published use cases (e.g. Metsä case) using the codes created for question four.

As the second step, the author focused on understanding how process mining is implemented. The same methods and logic have been used for this phase, but additional codes are designed.

Table 3 Table 6 Design of Codes Used for Qualitative Method Part Two.

Question	Elements to be coded	Codes
5. How process mining is implemented and adapted?	Implementation and adaption of process mining.	Technology People Implementation Resources Data Target, goal Leadership Lesson learnt

The success factors listed in Deloitte's survey are used while designing the codes. Based on the codes, the author analyses the use cases to understand how the companies implemented process mining and what they learnt.

Patton M.Q. describes working with qualitative data as an art and science that requires critical and analytical thinking and an innovative perspective. (Patton, 1990) The author tried to take a critical and analytic approach to analyse the given data and create an operating model in this research. However, it is also important to mention that the author has experience in the field; therefore, subjective points of view may exist in the research. (Saunders et al., 2009)

3.3 Reliability and Validity

Reality and validity are concerned with trustworthiness, rigour and quality in qualitative research. (Golafshani, 2003) Research's truthfulness and bias impact the trustworthiness, rigour and quality. (Denzin, 1978). Even though the research is designed to use the triangulation technique to decrease the risk of validity (Creswell and Miller, 2000), certain biases may exist while selecting data sources, analysing data, and concluding the results.

Selection of use cases: The study analysed five use cases selected based on adoption trends in the field. However, the cases are proven to provide the best insights, or the results could be different if other uses cases are used.

Selection of Source: The study used market researches and surveys conducted by different companies. The companies may be selected based on the researcher's personal experience, data availability and access. Even though the author believes the companies are independent and recognized as trustworthy researchers in the industry, they can be accepted as secondary data only, and subjectivism needs to be considered.

Subjective Bias in Conclusion: The research is concluded based on the researcher's analytical and critical thinking skills. Even though the author tried to use objective analysis and validate the outcomes with multiple resources, there is still a place for bias in judgement.

4 PROCESS MINING CAPABILITIES AND USE CASES

In the beginning, most efforts related to process mining has been focused on process discovery. However, it has been realised that process mining provides more than the discovery of the process. In time, the efforts were distributed among conformance checking, performance analysis, process improvement, prediction, and recommendation by combining other areas such as machine learning and RPA. Also, the application of process mining has expanded from The Order-to-Cash and Purchase to production, logistics, healthcare, energy systems customs, security transportation, user-interface design, smart homes, airports (Van Der Aalst 2020). In 2016, Van Der Aalst stated that they applied process mining in over 150 organisations, including municipalities, high tech manufacturers, health care, and more back in 2016. (Van Der Aalst, 2016).

As discussed in chapter 2, process discovery aims to understand as-is processes. It helps to discover the process by providing process structures, frequent behaviour, possible paths that can be followed, and their frequency. (Ailenei et al., 2011) Once a process is discovered, different activities such as checking, detecting, comparing, diagnosing, enhancing, predicting, and recommending can be performed.

This chapter will answer the first research question, "*What value can mining bring to organisations?*" by analysing different process mining capabilities and use cases.

4.1 Process Mining Capabilities

Gartner Defines operational support systems as a "set of programs that help a company monitor, control, analyse and manage computer network". (Gartner, 2021) In the context of process mining, operational support help support detect deviations, predict events, and recommend actions at run time by using data of partial trace current data). (Lamghari et al., 2021). In other words, detect, predict and recommend actions targeted to influence a process while still being executed. (Van der Aalst, Pesic and Song, 2010)

Operation Support techniques replay partial data to detect deviation at run-time by comparing the partial trace to the model, and it can generate alerts before the trace is completed. The techniques can also make predictions and recommendations by comparing the current case to similar cases recorded in the past. The predictions can be related to time, actions, possible expected actions or results. (Van Der Aalst, 2016) while recommendations can be related to the following actions. The operation support can help react to undesired situations timely, to select the right resources based on predictions and recommendations. (Lamghari et al., 2021)

The refined process mining framework categorises the activities which can be performed using process mining into three categories: cartography, auditing and navigation. (Van Der Aalst, 2016) These categories are extended to Performance Analysis, Comparative Process Mining, Predictive Process Mining, Action-oriented process mining, Robotic Process Automation, Automation, Machine Learning, Extracting, Filtering and Cleaning Event Data.

4.1.1 Cartography

Cartography activities use historical data and as-is processes to discover, enhance and diagnose. The discovery activity generates business process maps describing the operational processes. Having accurate and interactive process maps means having transparency on what happens. (Van Der Aalst, 2009) Transparency enables the organisations for better process re-design, workflow optimisation, activity automation, thus increasing the efficiency of business processes. (Reinkemeyer, 2020). The diagnose activities help to see the full spectrum from high-frequent to low and from automated to manual; this can be used to identify RPM candidates. (Van Der Aalst, 2020). The diagnosis can also help detect deviations in the process that helps to pursue coherence. (Faizan, 2020.) After discovering the process and detecting the deviations, the process can be enhanced, repaired or extended based on improvement potentials. (Boenner, 2020)

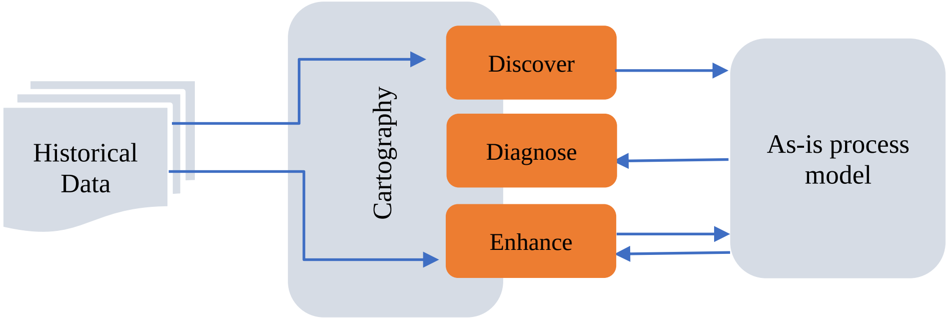

Figure 13 Cartography

The cartography activities help to identify process evolution and needed customisation. Thus, it helps to enhance the model according to changes on a producer, changes in people behaviour in various external circumstances and customisation needs. (Fahland and Van Der Aalst, 2015)

4.1.2 Auditing

Auditing uses historical and current data to compare differences between as-is and desired processes, check and detect deviations, and promote the best practices in the as-is model to the desired model. Auditing activities contribute to revealing issues that might cause violation of compliance regulations, help to check if the process is executed within the boundaries set by governments and other stakeholders. (Van Der Aalst, 2016) It also contributes to identifying process-related risks by visualising the process and detecting deviations in run time. (Boenner, 2020) Moreover, it makes outperformers visible, increasing the possibility to lesson learnt and knowledge sharing. (Jansen, 2020)

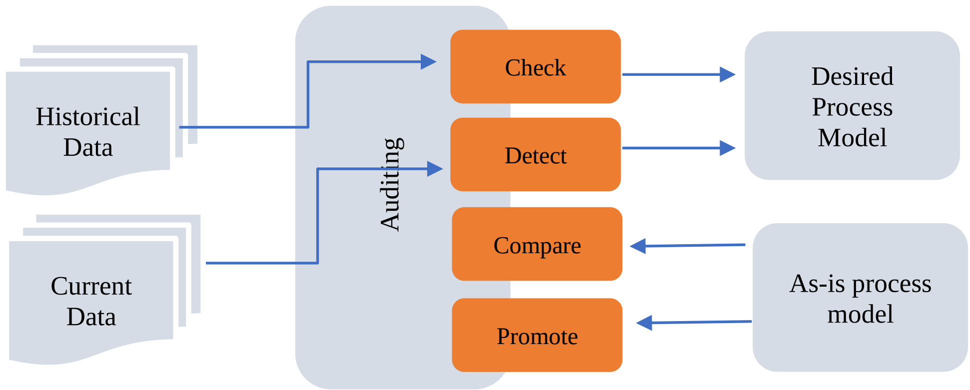

Figure 14 Auditing

Organisations need to perform auditing in several contexts: financial, health and safety, ethical conduct, and quality. Process mining can support auditing by comparing the processes against documented processes. (Lamghari et al., 2021) The success of auditing with process mining relies heavily on how well the process is documented and how the terminology among different expert groups such as IT, Audits, Compliance, Business experts are used. (Roubtsova and Wiersma, 2018)

4.1.3 Navigation

Navigation activities use current data to explore, predict, and recommend the desired model; the attention is shifted to current data with more forward-looking. (Van Der Aalst, 2016) Process mining aims to predict pre-defined targets with the usage of activities from the running cases. Several studies suggested focusing on prediction of next event, business process outcome, service level agreement violations, remaining time, activity delays, cost. (Mehdiyev and Fettke, 2021)

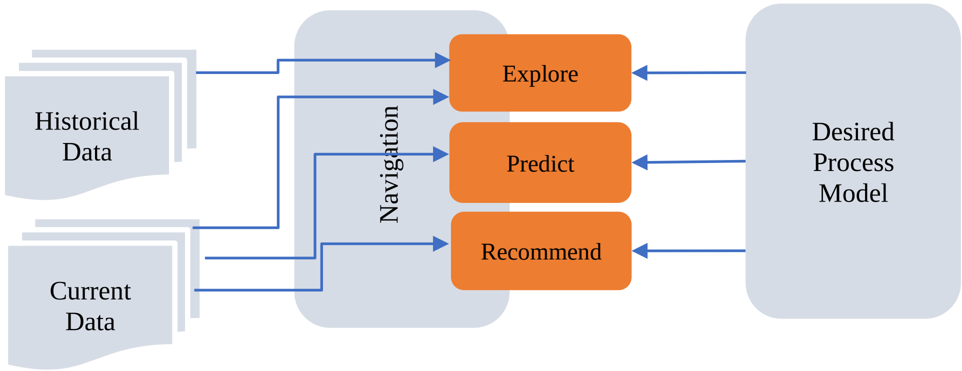

Figure 15 Navigation

4.1.4 Run time Detection

Detect is one of the operation support activities that focus on detecting deviations and violation on run time. It compares the partial trace with a normative model and creates an alert when a deviation is detected. Conversely, conformance checking focuses on one particular case, and an immediate response is expected when a deviation is detected. (Van Der Aalst, 2016)

4.1.5 Run Time Predictions

Predict is an activity of operational support learns from a predictive model generated based on historical event logs and a partial trace of a running case to provide a prediction. (Van Der Aalst, 2016). There are several studies related to the prediction on time, cost, manufacturing, resourcing, etc. Studies show prediction activity in process mining can answer questions such as “what is the activity of the next event?”, “who is the resource triggering the next event?” (Pravilovic, Appice and Malerba, 2013), “When will this case be finished?”, “How long does it take before activity A is completed?”, “How likely is it that activity B will be performed in the next two days?” (Van Der Aalst, Schonenberg and Song, 2011)

4.1.6 Run time Recommendations

Recommend, similarly to predict, learns from historical event logs and recommends what to do next. The recommendations may be related to control flow, time and organisation perspectives but always concern specific goals. (Van Der Aalst, 2016). The operational support system can recommend actions and provide dynamic optimisation to have cheaper or faster activity variation, move a resource from one case to another, change prioritisation, better planning storage places etc. (Tu and Song, 2016).

4.2 Process Mining Applications

As mentioned in chapter 3, process the efforts of process mining related work were distributed among other types of process mining than the discovery. According to Gartner's study, adoption of the enhancement increases by 17% in 2021 compared to 2017, while the main focus still remains on discovery.

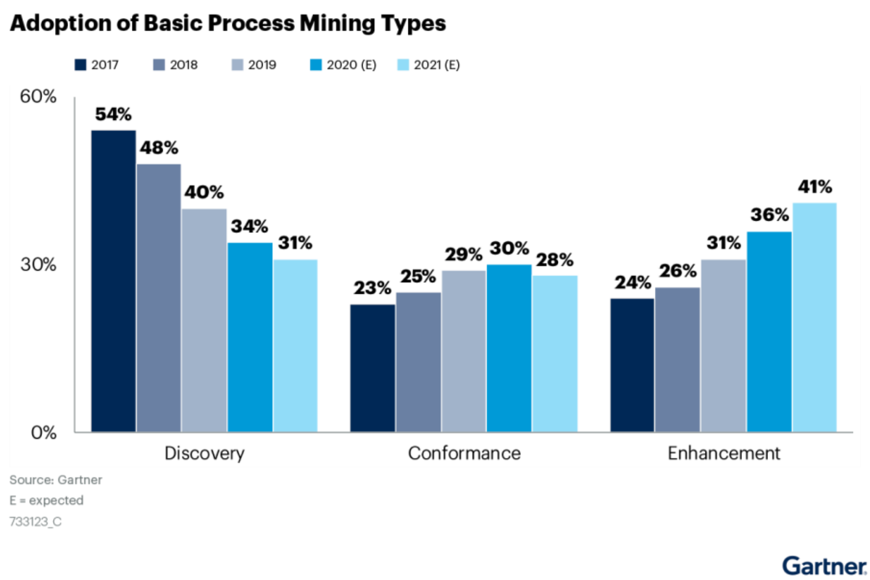

Figure 16 Gartner Adaption of Basic Process Mining Types

In the same study, Gartner also states that in 2018 and 2019, process mining initiatives mainly targeted business process improvement while process automation and robotic process automation initiatives are expected to increase by 2021. The study also marked task automation, digital transformation, artificial intelligence (AI) and Hyperautomation as the main drivers to adapt process mining in the future. (Kerremans et al., 2020)

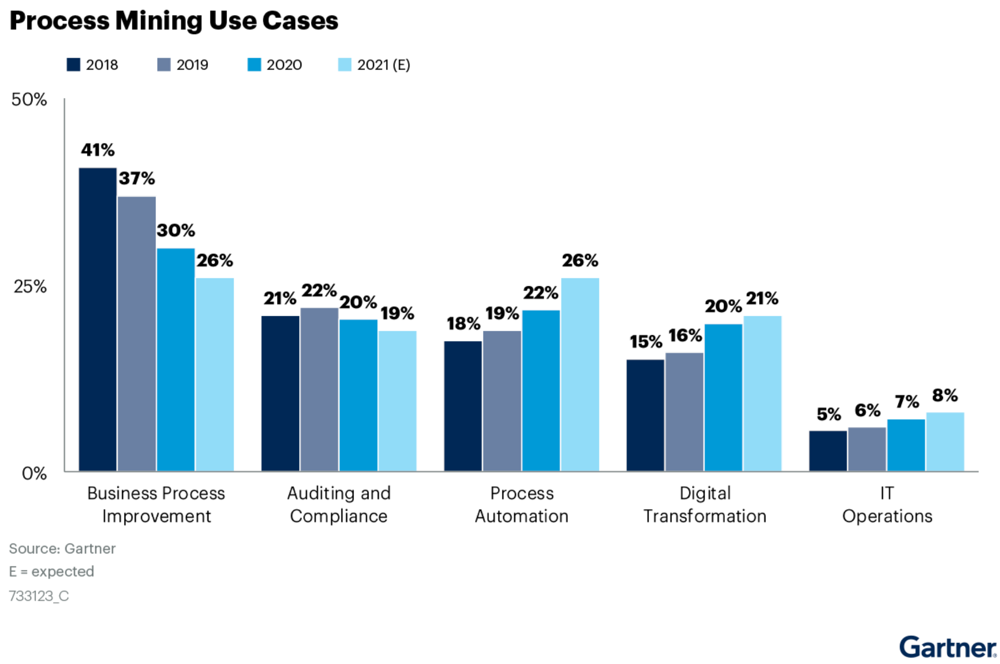

Figure 17 Gartner Process Mining Use Cases

Another essential angle is how the adaption is improving through different industries and sectors. According to the HSPI process Mining application database (updated in 2021), process mining has been applied in various industries and sectors (see figure 18). Among these industries, Financials by 17%, Healthcare by %15 and Industrials by 22% are leading using of process mining tools and techniques. Within these industries, organisations operating in sectors banking, manufacturing, healthcare facilities, services, and equipment have the highest usage of process mining. (Cotroneo et al., 2021)

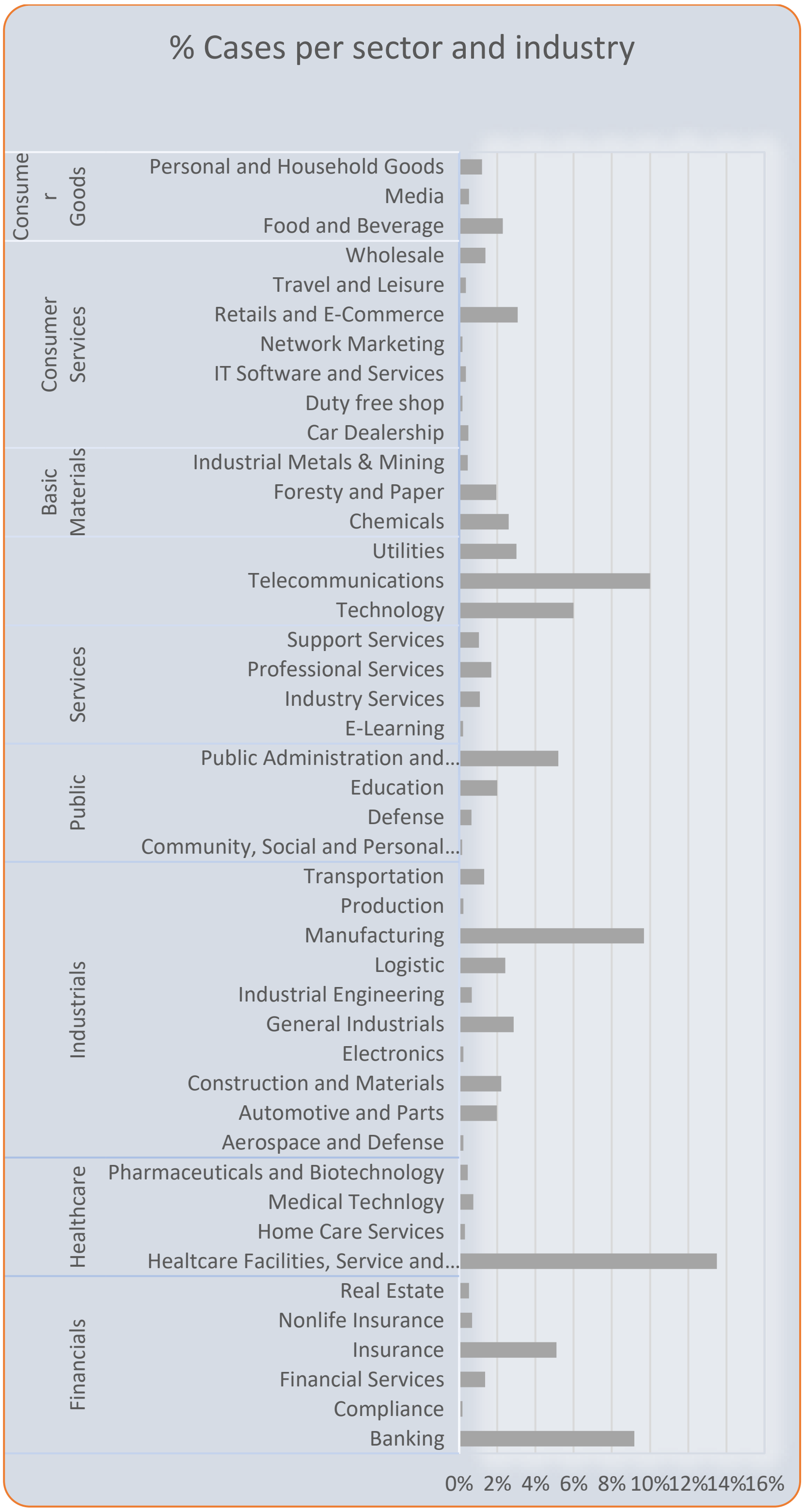

Figure 18 HSPI Process Mining applications, per sector and industry (Created based on data published on Cotroneo et al., 2021)

When the HSPI database is analysed throughout the years, it becomes visible in the early years (2008 to 2012); the projects are run mainly by academia to understand the capability of process mining for discovery and conformance checking of the processes in public and healthcare industries. From 2011-2012, projects extended to financials, industrials, consumer goods and services industries. During 2013-2014, there started to be more projects to identify deviations, unexpected behaviour between as-is processes and event logs. Benefits such as transparency, cost and time saving, increased customer satisfaction, production efficiency, and improvements in service management became visible. The focus on business process improvement continued in 2018-2019; since these years, there have been more projects with business analytics technologies such as Qlik Sense (e.g., MEHRWERK, Siemens Healhineers project 2020), RPA (e.g., Puzzle Data, Seoul Semiconductor project, 2019), and AI (e.g. MEHRWERK GmbH project 2020), as can be seen in Gartner's report also. (Figure 17). Several cases stated that they collect recommendations based on process mining findings in the database. Still, it is unclear if they used an intelligent technology/system capable of recommending or predicting at run-time. (Cotroneo, 2021).

The following chapter will analyse a few cases from different industries that targeted Process Improvement, Digital Transformation, Process Automation, Auditing and Compliance, IT Operations and a case where process mining contributes to continuous improvement culture. First, we will look into what the service provider company offers to their customers and analyse each case to understand the following points: problem definition, use case, solution, the impact of process mining related to each use case.

4.2.1 QPR - Metsä Case: Process Mining Order to Cash Process Improvement and Monitoring

QPR is a Finland based company that provides process mining solutions to its customers in over 50 countries. QPR lists their services/capabilities as shown in table 2. (QPR, 2021)
According to Gartner's survey, QPR focuses on business process improvements, improving process automation opportunities uses cases. QPR also focuses on providing real-time dashboards with support for KPI capabilities. (Kerremans et al., 2020)

Table 4: QPR Process Mining (QPR, 2021)

Offered Services	Description
Interactive Process Visualisation	It helps to visualize the processes automatically.
Identification of bottlenecks, rework, variation	It helps to identify problems and improvement opportunities.
Root cause Analysis	It helps to identify the root causes
Automation opportunity Scout	It helps to identify automation opportunities and simulate the impact of the automation.
Bot, workflow and automation activations	It helps to monitor automation and initiate corrective actions.
AI-based predictions for KPIs	It helps to predict and prevent failures.
Business alert and notifications	It helps to notice KPI breached and violated rules.

Metsä is Finland based company in the forestry and paper sector. QPR and Metsä started to work together on Metsä's Order-to-Cash process. (Cotroneo, 2021)

Problems are defined as follows:

- Out-dated ERP that does not reflect current business structure
- No means of measuring process performance and identifying deviations
- Lack of transparency on business operations reporting

Use Case/Solution:

In 2011 – 2012, a project started to analyse the current processes (what – how – why), then focus on re-engineering the processes and continues monitoring to ensure the processes run as designed. Metsä added analysis again to the scope in addition to continuous monitoring for new opportunities in changing environment. (Ketonen, 2018.) QPR provided a solution to improve process performance using data, identify bottlenecks for process automation, and discover the root cause for the problems in the process. (QPR, 2021)

Impact, business benefit:

- 40% increase on conformant order lines. (QPR, 2021)
- 60% increase or order lines and volume (QPR, 2021)
- Mitigated geographical handicap (QPR, 2021)
- Improved process performance. (Ketonen, 2019)

- Easier identification of the areas to improve and easier change management as the need for changes is proven with data and facts. (Ketonen, 2019)

4.2.2 Celonis – ABB: How Process Mining contributes continuous improvement culture

Celonis is the first commercial process mining company founded in 2011, and currently, its process mining tool is used by 500 companies. (Celonis, 2021) According to Gartner's survey Celonis focuses on digital transformation and business process improvement cases. Celonis also focuses on developing new innovative capabilities, such as task mining. (Kerremans et al., 2020) Celonis lists their services/capabilities as shown in table 3. (Celonis, 2021)

Table 5: Celonis Process Mining (Celonis, 2021)

Offered Services	Description
Real-Time Data Investigation	It provides real-time task and process transparency, identification of gaps.
Process and Task Mining	It provides a full possible view of processes, including user interactions.
Pre-built analyses and models	It provides out-of-box analysis, models and benchmarks.
Visual and Daily Management	It delivers insights, prioritised tasks, recommendations, suggestions on automation.
Action Flows	It provides the ability to execute and automate actions across all systems
Planning And Simulations	It provides a platform to model and simulate to-be processes to see the impact of decisions

ABB is an international company in the Power and Automation sector. ABB aims to use process mining as technology to support businesses to identify opportunities and risks. (Jansen, 2020). ABB utilised process mining various processes such as procurement, accounting, logistics. Celonis supports ABB to improve efficiency, speed, and cost-saving on various processes. (Cotroneo, 2021)

Problems:

ABB has many different processes considering various product portfolios and a long history of merging and acquisitions. The processes are run and managed on different platforms and generate massive amounts of data. (Jansen, 2020). However, their challenges have been mainly technicalities on how to execute the improvement projects in such an environment (as below) as ABB has well-established continuous improvement culture. (BearingPoint, 2019)

- Connecting various platforms with easy interfacing and managing significant amounts of data. (Jansen, 2020).
- Improved real-time analysis. (Jansen, 2020).
- Utilising and harmonising master data. (Jansen, 2020).
- Low dependency on the various domain architecture. (Jansen, 2020).

Use Case/Solution:

ABB aim to improve their lead time and on-time delivery and in time. As the first step, discovering potential problems taken, questions such as “how are payment terms aligned with actual payments, what is slowing down the delivery processes towards customer processes, where do have low utilisation of resources? “(Jansen, 2020). Furthermore, according to Martin Scgaedler, IS Manager Global BU High Voltage, Celonis was able to help answer these questions. For example, ABB was able to identify redundancies in their purchase-to-pay processes and the root cause of the redundancies. Celonis helped ABB to improve the process, reduce waste and become faster. (Celonis 2017).

After the first phase, discovering the potential problems, ABB focused on creating optimum performances, improving utilisation of resources, and identifying the most optimal mix between customer service and cost. Furthermore, on a later stage, ABB work on the questions such as “how to improve the overall lead time through the entire e2e supply chain?” and extended data models and analytics on the processes such as Opportunity Management, Planning and Fulfilment, Procurement Logistics, Shop Floor Management etc. (Jansen, 2020).

ABB also extend process mining scope eliminating the activities that are not contributing to the process and identifying automation opportunities to improve efficiency. They started using insights on processes in different factories, units, countries that help with benchmarking to learn best practices and shared the knowledge across units, countries, factories. (BearingPoint, 2019)

Impact/Business Benefit:

- Improved Lead time in various processes. (BearingPoint, 2019)
- Benchmarking factories to learn best in practises process, developing process improvement community where employees can collaborate. (Celonis, 2017)
- Getting reliable and faster help with a competitive edge (Celonis, 2017, BearingPoint, 2019)
- Empowering people and influencing business results directly from processes themselves. (Celonis, 2017)
- Identifying high redundancy in processes, finding the root causes and optimising the processes accordingly. (Celonis, 2017)
- Executing improving projects much faster. (BearingPoint, 2019)

4.2.3 MEHRWERK GmbH – Siemens Healthineers: Process Mining in Digital Transformation

MEHRWERK GmbH is a company founded in 2008 that provides data analytics solutions. (MEHRWERK GmbH, 2021) Later, the company started to offer MEHRWERK Process Mining solution as a part of business intelligence, supply chain management and SAP Cloud solutions. According to Gartner's survey, MPM focuses on business improvement, digital transformation, and it can use all capabilities of Qlik BI as it natively runs on Qlik's BI platform. (Kerremans et al., 2020) MEHRWERK GmbH lists its services/capabilities as shown in table 3. (MEHRWERK GmbH, 2021)

Table 6 MEHRWERK Process Mining (MEHRWERK GmbH, 2021)

Offered Services	Description
Process Visualisation and analysis	It visualises and analyses the processes
Conformance Checking	It helps to understand how wee actual process perform compared to the target process.
Process Monitoring and process prediction	It helps to monitor ongoing processes and predict the process development.
Action and Workflow Management	It distributes actions directly from MP to employees or RPA bots
Root Cause Analysis	It helps to identify the root cause of inefficiencies.
Process Harmonisations	It helps to harmonise processes across different units.
Compliance	It helps to ensure compliance requirements
Product Optimisation	It helps optimise processes in terms of time, cost and process stability.
Digital Transformation Impact Controlling	It helps to measure digitalisation progress
Process Automation	It helps identify RPA potentials
Qlik BI (Business Intelligence) Capabilities	It integrates BI capabilities.

Siemens Healthineers is a Germany based company that provides healthcare products, services and solutions globally. (Siemens, 2021) Siemens Healthineers adopted process mining applications in the productive business platform (Reindler, 2020). Process mining was introduced as part of the digitalisation strategy to identify long lead times, process deviations, and bottlenecks. (Cotroneo et al., 2021)

Problems

Siemens Healthineers developed a solution to control large medical devices with a mobile tablet control system that created more flexible working conditions for health care specialists than static computer workstations. The specialists use both static workflows and mobile control systems, making it challenging to view workflow steps from 2 different technologies. (Reindler, 2020)

- Two different technology generated different event logs for the same actions. (Reindler, 2020)
- Different teams design the technologies, and this requires alignments on data structure, consistency and completeness between the colleagues. (Reindler, 2020)
- The challenges above reflected on the transparency of the workflow. (Reindler, 2020)

Use Case/Solutions:

Siemens Healthineers started using process mining solutions to understand how specialists work with medical devices to gain valuable product management insights (Reinkemeyer 2020). Reinder explains the goal of having a valid and robust IoT database to analyse the devices and discover actual user behaviours and variants in the process. (Reindler, 2020)

One of the identified challenges was unstructured, non-standardised data; the project team identified differences in terminology, key identifiers, and even definitions. The project team also analysed different activities in the workflow, and they started to have visibility on process variants, number of exams per day, cycle times. They solved the data quality issues by re-structuring the databases based on the learning of the workflow mining. (Reindler, 2020)

Impact Business Benefit:

- Standardised CT workflow based on actual customer activities by uncovering process variants. (Reindler, 2020)
- Connected heterogeneous data sources which provided event logs from IoT data, among others. (Cotroneo et al., 2021)
- Improved lead time analysis. (Reindler, 2020)
- Reduced workflow times by automating workflow based on manual and automated stages comparison. (Reindler, 2020)
- Providing complete transparency. (Cotroneo et al., 2021)
- Creating a competitive advantage as Siemens Healthrineers helps implement fast learning cycles to improve operating software. (Reindler, 2020)

4.2.4 Minit – A logistic Company: Process Mining for identifying RPA opportunities

Minit is Slovakia based company focusing on continuous process improvement and operational efficiency. Minit lists its services/capabilities as shown in table 5. (Minit, 2021) According to Gartner’s survey, Minit focuses on Improving Process Automation and IT operational resource optimisations use cases more than other process mining service providers. (Kerremans et al., 2020).

Table 7: Minit Process Mining (Minit 2021)

Offered Services	Description
Process Analysis and optimisation	It analyses the as-is process and gets a baseline for process improvements
Process Discovery and mapping	It helps to identify as-is processes
Process Audit and Compliance	It provides data-driven process audits and compliance
Process Simulation	It helps to simulate changes in the process and identifies the best optimisation options
Process Compare	It helps to identify best-performing processes
AI.Powered Root Cause Analysis	It helps to uncover problems and investigate why the problems occur
Robotic Process Automation	It helps to identify potential candidates for RPA.

Minit did not share the company's name for the RPA case they had executed. The only information published in the sector industry of the company, which is Logistic. Therefore the study is limited to only information shared by Minit.

Use Case/Solution

Minit worked with a logistic company to automate invoice approval processes. (Cotroneo, 2021). Minit provided baseline process information and cost overview and identified activities that are rule-based, standardised with few exceptions. (Minit, 2021)

Impact/Business Benefit

Minit has shared the details below as a benefit their customers gain:

- Three hours reduction in mean case duration. (Minit, 2021)
- Approximately 466K Euro savings in five months. (Minit, 2021)

4.3 Results and Conclusion

This chapter focused on understanding the value process mining can bring into companies by looking into different capabilities and use cases. Process mining is used for many cases for different purposes as studies and published use cases are presented. As seen in the HSPI database, it has been applied in various processes in different industries and sectors. (Cotroneo, 2021).

Many of the use cases presented process mining helped companies improve their processes, generate savings, reduce operating times, improve efficiency and productivity, automate tasks, take actions based on conformance and performance diagnosis to address the identified problems. The chapter also included what service providers offer related to process mining.

Although published use cases provide great insight, they are mainly focused on success stories, as may be expected. Therefore, it is challenging to understand what companies are initially expected to gain from process mining, what process mining vendors have promised, and the actual result, especially in failure cases. Some use case examples mention setbacks related to high and quick results expectations (e.g. Buhrmann, 2020) and how important it is to have realistic expectations (e.g. Lillig, 2020). Reinkemeyer also mentioned that many project mining projects fail because of exaggerated promises, unrealistic expectations, among other causes. (Reinkemeyer, 2020).

It is helpful to understand what can be expected from process mining without additional effort (direct benefits) and what can be expected based on actionable insights process mining provides (indirect benefits). (Galic and Wolf, 2021). Moreover, how these benefits are reflected in use cases and how companies gain direct and indirect benefits. As seen in figure 19, it starts with discovering the process and gaining actionable insights. The companies need to develop directions that align with their strategies to impact their business.

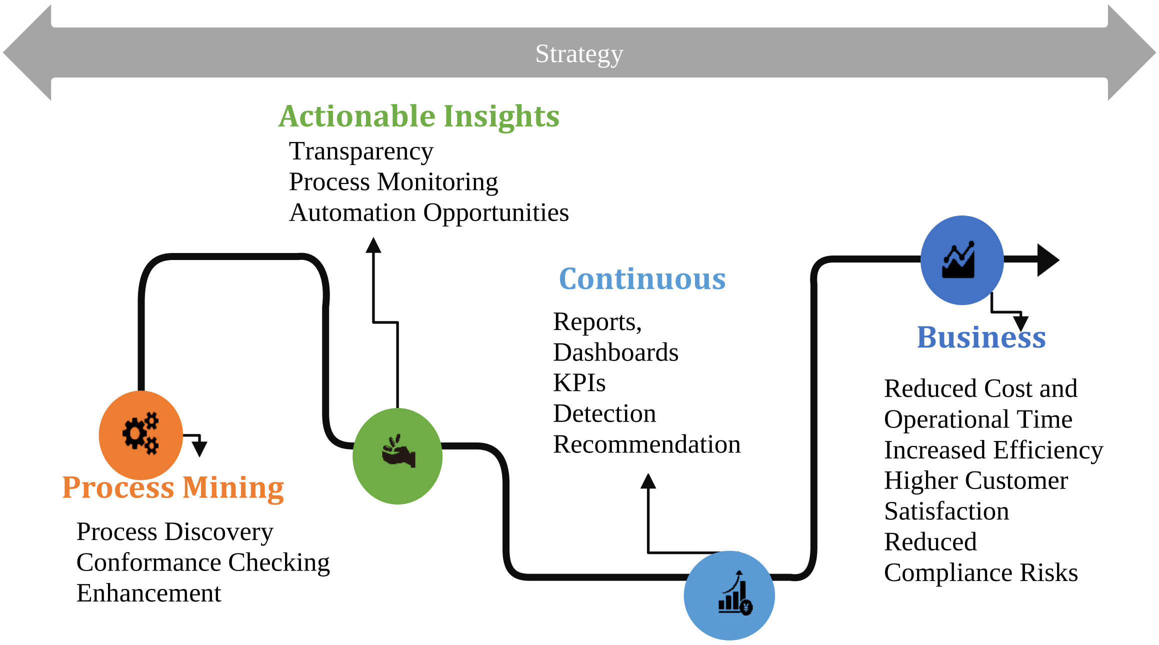

Figure 19 Process Mining: from mining to impacting the business

The paper categorised process mining applications into eight groups based on existing use-case examples and capabilities identified by academia and service providers: 1. Discovering Process Models, Exceptions, bottlenecks, 2. Conformance Checking and Gap Analysis, 3. Process Model Enhancement, 4. Improving Customer Experience, 5. Identifying RPA Opportunities, 6. Improving Data Quality, Data preparations, Data Clean-Up, 7. Views, Monitoring, and Reporting, 8. Predictive Analytics and recommendations.

4.3.1 Discovering Process Models, exceptions, bottlenecks

Process Discovery is the starting point of process mining and will remain important. (Reinkemeyer, 2020) As seen in figure 16, many process mining uses cases are still related to process discovery. Many studies and cases show that process discovery is essential as it provides complete transparency on the as-is process. (Reinkemeyer, 2020). Transparency also makes process mining a fundamental enabler for automation potentials and artificial intelligence use cases. (Apitzcsh, 2020)

Companies can reduce overall flow time by Identifying exceptions, identifying bottlenecks as these discoveries may trigger re-designing the processes. (Van Der Aalst, 2016). Over thirty use cases in the HSPI Process Mining database include identifying bottlenecks, exceptions, long lead time or lead time delays, common process variants, detailed time, and cost to serve. Based on these insights, the companies were able to reduce errors and delays and save operational costs (e.g. an unknown customer of StereoLogic, Canada, 2017), eliminate bottlenecks (e.g. Fiducia, Germany, 2014), cut customer service response time and reduce error rates (e.g. Otney Bowes Inc, USA, 2013), improve transparency, reduce process variants (e.g. an unknown customer of Lana Labs GmbH, Germany, 2019). (Cotroneo, 2021). The benefit of process discovery also has been recognised in Celonis - ABB case. ABB indicates, it is easier to drive change when the need for change is proven with data and facts.

4.3.2 Conformance Checking and gap analysis

Conformance checking is used to compare as-is processes and desired processes. In 2016, Van der Aalst suggested that It can be used for auditing and compliance. (Van Der Aalst, 2016). Alternatively, it can be used to audit any process to reduce undesirable properties in a process. (Van Der Aalst, W.M., 2020) Moreover, many process mining vendors list it in their capabilities. HSPI Process Mining Database includes over fifteen auditing cases. Some companies are using it as part of their internal auditing process, e.g. ING (Netherlands) uses process Mining to detect policy violations and unusual transactions, or Deutsche Post DH Group (Germany) to reduce the audit time. Some companies use process mining for auditing IT systems in systemic ways; others use it to improve processes. The companies also use conformance checking to identify execution gaps, e.g. Bonfiglioli (Italy) and Innogy (Germany). (Cotroneo, 2021). In some cases, it is also used for benchmarking. For example, in the ABB case, they were able to identify the differences in processes between countries, units and newly acquired subsidiaries.

According to Gartner’s survey, process mining vendors ABBYY, Appromore, Labs, EverFlow, MEHREWERK focus on conformance checking and gap analysis more than other vendors. (Kerremans et al., 2020).

4.3.3 Process Model Enhancements

Figure 16 shows that the adoption of enhancement has increased in recent years. Insights gained by process mining helps companies to enhance their process models. (Schukat, 2020). In HSPI Process Mining Applications Database, there are examples of companies from various industries that targeted to enhance processes, e.g. DSME (Korea) targeted to enhance process models of shipbuilding block assembly, Samsung Heavy Industries (Korea) targeted pipe production process. (Cotroneo, 2021).

According to Gartner's survey, process mining vendors Apromore, Integris, Puzzle Data focus on model enhancement more than other vendors. (Kerremans et al., 2020).

4.3.4 Improving Customer Experience

The importance of Customer Journeys became more visible in recent years to understand the complex customer behaviours and get insights into their experiences. (Tueanrat, Papagiannidis and Alamanos, 2021). This trend reflects in the field of process mining. In the Process Mining conference (2019), participants considered the customer journey one of the focus areas in process mining. Process mining can provide a trace of customer's interaction, thus insights to understand customer behaviours. Understanding customers' behaviour provides insights to improve customer satisfaction, and help predict following actions, possible delays, the result of the process. (Reinkemeyer, 2020)

In HSPI Process Mining Application Database, various cases discussed customer journeys, e.g. Telefonica (Spain) was able to map customer journeys completely with process mining and optimise based on insights gained. (Cotroneo, 2021). Another example is how Uber uses process mining primarily to improve customer satisfaction. Process mining helps them use data for analysing processes with high speed, overseeing all support specialist interactions. Process mining helps Uber see improvement opportunities quickly, find hidden inefficiencies, identify the best practices and automate. (Rowlson, 2020)

4.3.5 Identifying RPA Opportunities for tasks

In 2017, Deloitte ran a survey related to the use of RPA with over 400 responses; according to the survey, near half of the respondents indicated RPA did not deliver planned improvements. (Deloitte, 2018). Many articles listed the wrong choice of automation as one of the causes of the failure, among other causes. (e.g. Lawton, 2020). Some articles also listed "automating too much of a process" and "not optimising for RPA" as failure types of RPA. (Money, 2021).

Many studies show that RPA is feasible for repetitive, time-consuming, error-prone, rule-based processes and does not require human judgment (Myteberi, 2019). Process mining can support RPA projects and services to visualise and select processes that can be automated. Process Mining discovers inefficiencies, the frequency of activities, and exceptional cases requiring human interactions or need to be handled ad-hoc. (Van Der Aalst, 2019) It is essential to evaluate the discoveries for automation potential to avoid inefficient process automation. Nevertheless, combining process mining and RPA seems to be a beneficial approach the mitigate the risk of inefficient process automation and unveil potential savings. (Buhrmann, 2020)

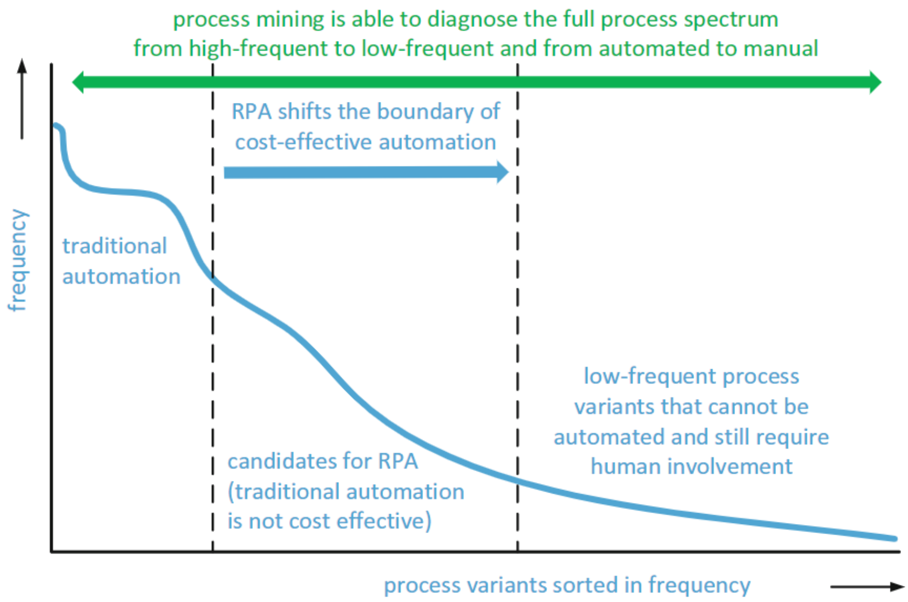

Figure 20: Process Mining – Potential RPA Candidates. (Source: Van der Aalst, 2020)

HSPI Process Mining application database includes around ten cases that process mining is used to select RPA candidates in the manufacturing (e.g. Seoul Semiconductor – Puxxle Data Business Impact, 2019), logistic (e.g. Minit 2019), telecommunication (e.g. National Coverage Telco - Mobile and Fixed services, Icaro Tech, 2018) Finance (e.g. Canadian Real Estate Finance Company, StereoLOGIC, 2018) industries. Many of these cases indicated that they could reduce implementation time and errors and generate savings. (Cotroneo et al., 2021) In addition to time and errors, reduction and generating savings, Siemens uses RPA to monitor performance through process mining as RPA captures and sorts data much faster than humans. With that, they could have better data quality, increase RPA coverage and increase operational efficiency. (El-Wafi, 2020)

4.3.6 Improving Data Quality, Data preparations, Data Clean-Up.

Process Mining starts with data, and it is easy when the companies have perfectly structured and available data. However, in reality, data quality may be low, unstructured, or not even available. Process mining has been supporting the companies to bring transparency to their data quality, and Jansen K. stated,“ Trancepency on bad data is the only opportunity to improve it!” (Jansen, 2020) It is also understood that data quality is essential; identifying bad quality and improving the quality needs to be completed before analysing a process. (Lechner, 2020) There are several examples from companies that process mining help them improve data quality. For example, as seen Siemens Healthineers process mining projects were able to improve their data quality after it became visible with process mining with the help of the consultancy. (Reinder, 2020)

According to Gartner’s survey, process mining vendors Lana Labs, EverFlow, and Process Analytics Factory focus on data preparation and clean-up capabilities more than other vendors. (Kerremans et al., 2020).

4.3.7 Views, Monitoring and Reportings

Process Monitoring is one of the highest expected benefits of process mining. (Galic and Wolf, 2021) Almost all process mining service providers list process monitoring as one of the main capabilities. For example, Celonis Ultimate Process Mining Guide describes process monitoring as one of the process mining stages and explains the capability as “Measure the result of change and continuously surface new improvement opportunities” (Celonis, Celonis Ultimate Process Mining Guide, 2021); Minit describes their capabilities related to process monitoring as “monitor the length of the process time, the monetary cost spent on the process, as well as quality – errors and variations that affects delivery to customers.”. (Minit, 2021)

In the HSPI Process Mining Applications Database, many applicants indicate that companies monitor their processes against various Key Business Indicators (KIPs) or optimise their KPIs. For example, a retail company monitors sales performance, a construction company monitors their harmonised processes, and an automotive company monitors their account to payable processes. (Cotroneo et al., 2021)

4.3.8 Predictive analytics, Recommendations

As described in chapter 3, prediction and recommendations are listed as process mining capabilities in many resources and process mining manifesto. Several cases or feasibility studies (e.g. Mehdiyev and Fettke, 2021, Oliveira, 2020) use data from an organisation and study feasibility and benefits.

Some process mining service providers use machine learning and artificial intelligence algorithms to predict and recommend based on historical data. For example, Lana's predictive engine trains machine learning models to predict if a pre-defined activity will happen and remains time until it happens. These activities could be payment of invoice, delivery of goods, or early detection of ana activity cause a bottleneck. (LanaLabs, 2021) Appromore offers a plug-in to generate predictive models. The trained predictive models predict process properties such as next activity, remaining time and log specific case properties such as application cost. (Apromore, 2021). Although prediction and recommendations capacities are listed as capabilities, there is no application in HSPI Process Mining Database that shares any benefit in application results; they are case or feasibility studies or ongoing projects.

5 IMPLEMENTATION OF PROCESS MINING

Over the years, with more experience and knowledge, the implementation changed from small scale implementation projects to continuous forward-looking applications. (Van Der Aalst, 2020) For example, ABB has used process mining for over a decade and deployed it globally with its clear governance structure. (Jansen, 2020). ABB works with Celonis in every unit with a significant number of users. Local Units are empowered to improve their processes and global projects to improve and ensure collaboration between units. (BearingPoint, 2019). There are still many small scales or one-time projects being implemented, but the adoption of process mining keeps increasing.

In previous chapters, data and process models are defined as two components of process mining (chapter 2.2). Reinkemeyer, defined three pillars of success of process mining projects as purpose, people and process traces in an operational environment. (Reinmeyeker, 2020) This chapter explores these components, pillars, and other factors mentioned in use cases to understand how critical they are for process mining initiatives to succeed and extend.

5.1 Where to start

Van Der Aalst defines three types of process mining initiatives, data-driven, question-driven and goal-driven. (Van Der Aalst, 2016) All initiatives can work. However, success could depend on the maturity of process mining, the transparency of the processes in the company and clearly defined visions and incremental goals.

1) Data-Driven, Curiosity-driven: These are the initiatives that the stakeholders do not have a specific goal for the process. The focus is on understanding the as-is process and gaining insights from event logs. For example, in the QPR -Metsä case, their problem definition included “Lack of transparency”, and their starting point was to gain transparency. Only later, based on insights, they improve their process, eliminate bottlenecks and inefficiencies.
2) Question-driven: These are the initiatives driven by specific questions. In these cases, the stakeholders may already have insights related to their process. For example, in the Celonis – ABB case (described In chapter 3.2.2), ABB was already aware of a

delay in their delivery process. Therefore, they started with questions such as "What is slowing down the delivery processes towards customer processes?"

3) Goal-Driven: These are the initiatives driven by specific goals. For example, the Celonis – ABB case focused on a specific goal such as "How to improve the overall lead time through the entire e2e supply chain?". It is also important to note that they had to have some insights for ABB to see the need to improve lead time.

Companies need to start the initiatives with simple processes which is not very complex, areas where they can have quick results and where people are passionate about the changes. Even though process mining can be applied for many processes, it can be wise to start with processes that are proven to be quickly adopted, for example, P2P and O2C. (Reinmeyeker, 2020) Moreover, the scope can be extended incrementally based on insights, gained benefits, and lessons learnt.

5.2 Visions, Goals and Expectation Management

"Clear targets" is one of the critical success factors of process mining initiatives by many papers, researchers and experts. (e.g. Deloitte, Galic and Wolf, 2021) A successful project requires a clearly defined business purpose and is agreed upon by all involved. (Reinmeyeker, 2020)

Many methodologies and frameworks discuss the visions and goals of products and services. For example, the Scaled Agile Framework defines portfolio vision as an aspirational and achievable future state of a solution aligned with the company's strategy; solution vision what features and benefits the given solution provides. Moreover, specify iterations goals as business or technical goals that the teams agreed to achieve in an iteration. (specific time frame) (SAFe, 2021). Even if companies do not use SAFe (Scaled Agile Framework), this approach may apply well for process mining programs or projects. They can define a clear vision and reach it by achieving goals iteratively.

As mentioned earlier, process mining projects may fail because of unrealistic expectations, exaggerated promises. (Reinmeyeker, 2020) It may be that software vendors might be contributing the expectations that companies believe in unlimited possibilities of process mining. Deloitte survey's indicated that a very diverse set of expectations and some of the benefits could be achieved only indirectly based on insights gained from process mining and investing more in change management (changing the process etc.) or other technologies such as RPA. (Galic and Wolf, 2021)

In order to manage these high, sometimes impossible, expectations, it is essential to have a clear set of targets, be very transparent about risks and efforts and maybe use proven technologies. (Reinmeyeker, 2020) It can also be beneficial to use incremental frameworks (such as SAFe) to be more agile: start with a data-driven initiative to understand the status of the data and insights data can provide, focus on direct benefits and build on indirect benefits.

5.3 Data Management

Event Data data needs to be prepared to extract knowledge and gain value before using it for process mining. The preparation includes the following steps: Data Accumulation, Data Categorization, Data Cleaning, Data Reshaping, Data Storage. (Kourla, Putti and Maleki, 2020)

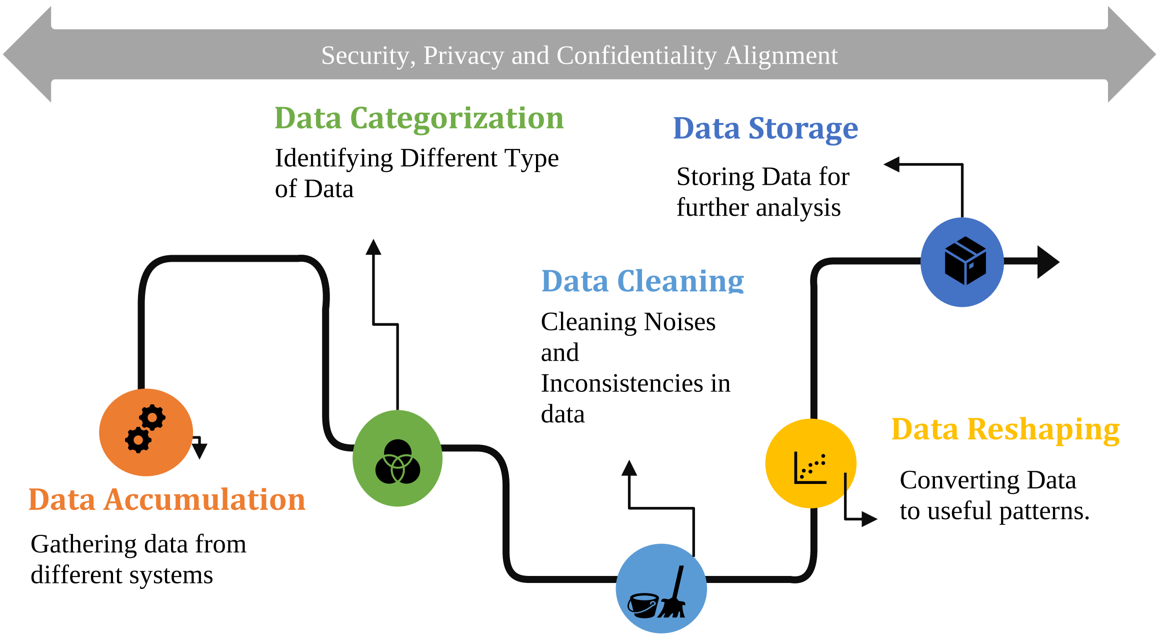

Figure 21 Knowledge Extraction from data (Inspired by Kourla, Putti and Maleki, 2020)

Process Mining Manifesto marks data extraction as one of the challenges of process mining. (Process Mining Manifesto, 2012). In many cases, data readiness seems to be taking 80% effort and time and applying process mining (Van Der Aalst., Gartner 2020). The reason could be that the data is scattered over various data sources because of technical or organisational reasons (Van Der Aalst, 2016). Moreover, data can be unstructured and non-standardised; there might be differences in identifiers for data properties, cases coming from different systems, or teams' design, as mentioned in the Siemens Healthineers case. These problems should not stop companies from using process mining can help improve transparency on data quality, creating an opportunity to learn and improve. (Jansen, 2020) It is also important to mention that data quality issues and their related risks must be transparent for all parties. To tackle challenges related to data, organisations need to have data governance in place to manage different aspects of working data.

5.3.1 Data Governance and Data Management

Data Governance is defined as:

> "Data governance is the specification of decision rights and an accountability framework to ensure the appropriate behaviour in the valuation, creation, consumption and control of data and analytics". (Gartner Information Technology Glossary).

Data Management is defined as:

> "Data management (DM) consists of the practices, architectural techniques, and tools for achieving consistent access to and delivery of data across the spectrum of data subject areas and data structure types in the enterprise, to meet the data consumption requirements of all applications and business processes." (Gartner Information Technology Glossary).

Based on the definition, it can be concluded that data governance is the entity to define organisation structures, data owners, policies, rules, processes, metrics and lifecycle of data. In other words, the governance model is the authority to work on how data solutions should be implemented. Therefore, it is essential to have a data governance model for any organisation.

Figure 22: The scope of Data Governance Source: Mosley et al., 2010.)

Data Management International Foundation (DAMA) defines the data management scope shown in figure 22. (Mosley et al., 2010) It consists of people, processes, technologies for the entire lifecycle and data usage that enables organisations to leverage the data. (Watson and McGivern, 2016) Undoubtedly, the governance scope and model can vary across organisations based on their needs and the regulations within their industry. Therefore, the organisations need to adapt and adjust the scope of the governance based on their needs. (Petzold et al., 2020)

McKinsey and the company shared a typical governance model structure with three components. Data Management Office is the function that defines policies and standards, ensures coordination across key roles, provide tools, playbooks, training. Data Council owns strategic directions and principles, and data leaders in domains own the data they created and execute strategy in their domain. (Petzold et al., 2020)

Figure 23 Components of a best practise Data Governance (Adapted from McKinsey and Company (Petzold at al., 2020)

5.3.2 Responsible Data Sciences from the view of confidentiality

There are many discussions about how a data solution should be implemented ethically and decrease the risk of harming any person, minority, or organisation. Responsible Data Sciences (RDS) focuses on four main challenges applicable to process mining: Fairness, Accuracy, Transparency, Confidentiality. (RDS, 2016). All these concerns and challenges are also valid for process mining; the companies need to address these concerns. (Van Der Aalst, 2020) The data governance body should be responsible for managing data responsibly.

Confidentiality is one of the aspects that needs to be considered strongly in process mining. There can be two main streams of confidentiality:

1. The companies may not want to share data and information for competitive reasons. (Process Mining Manifesto 2012)
2. Personal Data should be protected. In the EU, any organisation that processes people's data must comply with General Data Protection Regulations (GDPR). GDPR defines personal data as:
   "personal data means any information relating to an identified or identifiable natural person ('data subject'); an identifiable natural person is one who can be identified, directly or indirectly, in particular by reference to an identifier such as a name, an identification number, location data, an online identifier or to one or more factors specific to the physical, physiological, genetic, mental, economic, cultural or social identity of that natural person."

Process mining implementations have to consider data security, confidentiality and privacy from the very beginning. There should not be any data to identify an individual's behaviours and performance. (Mannhardt, Petersen and Oliveira, 2018). Even if the person would be anonymised, responsible data owners or workers counsellors should be consulted. (Reinkemeyer, 2020)

Privacy should be introduced by design has to consider rights of data subjects. (right to access, right to portability, right to oppose processes, and right to be forgotten). There are technological and organisational challenges that could be listed below. (Mannhardt, Petersen and Oliveira, 2018)

1. To minimise storage and process of the data while gaining insights.
2. To aggregate data guaranteed data privacy
3. To provide traceability to fulfil requirements related to the right to access, right to consent, right to be forgotten
4. To have a fully transparent, easily auditable process

5.4 People, Roles and Responsibilities

“People” is stated as one of the pillars of process mining (Reinkemeyer, 2020), and having dedicated resource availability is listed as one of the success factors for process mining. (Galic and Wolf, 2021). The role of people and different responsibilities in process mining also became visible in the study. For example, chapters 3.1.2 and 3.2.3 indicated how important it is when different resources, experts are aligned with terminology and how important it is to have different experts in the projects. Reinkemeyer suggested that the project team consists of business process experts, IT specialists, and external experts of process mining tools. (Reinkemeyer, 2020)

Process Mining project teams requires people, knowledge from different areas such as IT system experts, data specialists and analysts, data owners, process owners, business analyst (Fluxion Process Mining Book, 2020). Moreover, the projects need people responsible for running projects or scrum masters. It is essential to understand that the personas below may have different job titles. Based on the organisation set-up, multiple responsibilities can be held by one persona, steering committee or shared services.

1. IT System Specialist, Administrators: A persona with administrative skills to extract data from information systems or systems. (Fluxion Process Mining Book, 2020).

2. Data Specialists and Analyst: A persona design data gathered from different sources. (Fluxion Process Mining Book, 2020).
3. Process Analyst/Business Analyst: A persona generates process improvement ideas, analyse suggestions, an expert on process improvements. (Fluxion Process Mining Book, 2020).
4. Process Owner: A persona understands and owns the process, who is in charge of process design, improvement, and efficiency. (Reinkemeyer, 2020)
5. IT Application/Solution Owner: A persona responsible for solution design and development, innovations, road-map, planning, budgeting, and ensuring IT and Business collaboration. (Reinkemeyer, 2020)
6. Business Application/Solution Owner: A persona responsible for solution vision, collaborating with IT Solution Owner related to design, development, innovation, planning. . (Reinkemeyer, 2020)
7. Service/Support Experts: a persona responsible for application continuity, incident management and end-user support.
8. Security Expert, Legal and Compliance Officers: A persona consults the projects related to privacy, security, compliance, and ethics. (Fluxion Process Mining Book, 2020)

5.5 Sofware, Services and Technology

There are many vendors providing process mining software. Many of these vendors provide functionalities for many use cases. (Kerremans et al., 2020) The companies might have different criteria to select software and vendor or different expectations from the software and vendors. The criteria may include general software selection criteria such as license management, infrastructure and use related case criteria such as process mining types and operational support activities. (Drakoulogkonas and Apostolou, 2021) A study run by the Chair of Digital Industrial Service System lists essential software capabilities for process mining practitioners who used various process mining software as follows: (FAU, 2021)

1. Automated Data Validation and Cleansing
2. Ease of Data Extract, transform and load
3. Integrability

4. Multi-level process mining.
5. Ease of use
6. Customizable dashboards
7. In-built RPA and Task Mining Capabilities.

In addition to the seven criteria listed above, the five criteria below are typical decision-making criteria. (Reinmeyeker, 2020)

8. Performance
9. Stability
10. Scalability
11. Reference
12. Price

This list seems to be supported by several cases used by this study. For example, Deutsche Telekom Services selected a software provider based on SAP integration, high user experience, and proven use case with another company in the same sector. (Lillig, 2020) In addition to expected software capabilities, it is also realized that working with consultants is necessary to achieve the goal. As experts or consultants, companies will contribute with their knowledge gained over the years working with various companies and projects. (Reinmeyeker, 2020).

A vital architecture landscape is essential for sustainable process mining implementation regardless of the software used. (El-Wafi, 2020) Various factors drive the choice of system architecture/landscape; therefore, companies design their architecture based on their needs or environment. As mentioned in previous chapters, collecting and standardizing data requires significant effort, and the same data can be used for various purposes in different business units. Therefore, reusability of data is essential and proven valuable; it will prevent multiple teams, units from the double effort. (Reinmeyeker, 2020). Many companies apply multi-layer architecture that supports them in collecting and analysing unstructured data, enabling real-time processing and having cost-effective analytics capabilities. (Blumberg et al., 2017) Reinmeyeker L. (2020) shares a typical architecture used in companies below.

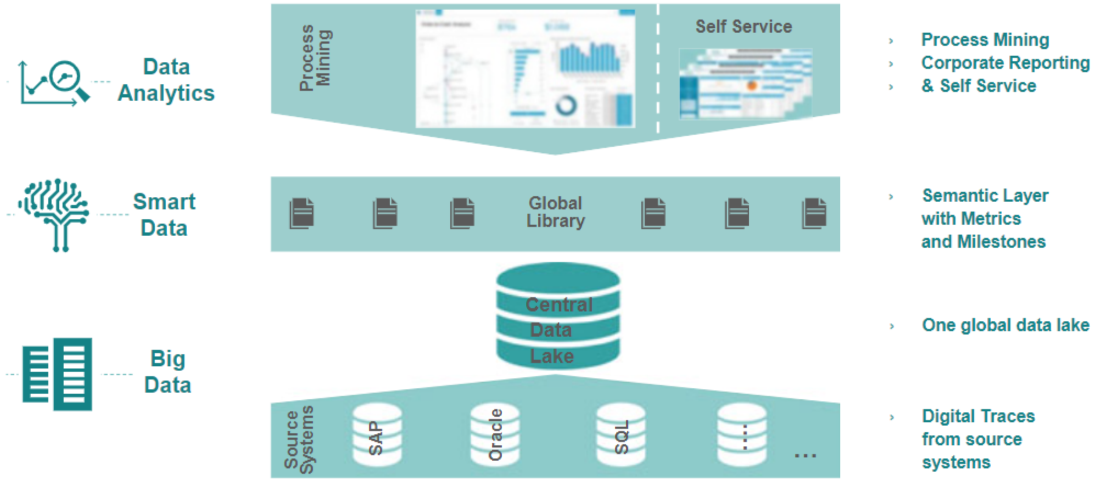

Figure 24 Typical Architecture (Source: Reinmeyeker, 2020)

5.6 Organisation and Governance Model

The study discussed and studied different scales of process mining implementations, from a project to globally extended process mining programs. Studies (e.g. Deloitte Process Mining survey) show that companies are planning to extend the usage of process mining to gain enterprise wised benefits. To scale process mining, building a governance structure driven by business value and an organization that supports cross-department alignment between IT and multiple business lines are essential. (Galic and Wolf, 2021)

A government model and an organization supported by leadership are key scaling process mining initiatives. They are essential in supporting the goals, common objectives, directions, identifying roles and responsibilities, creating continuous improvement culture and supporting change management. (Celonis – ABB case, chapter 3.2.2) (Jansen, 2020)

The companies have been using different models and organisational structures to scale process mining. For example, ABB has a business transformation governance model that includes a business board and technical support. ABB enables its experts in different units as part of their continuous improvement program with process mining capabilities. (Jansen, 2020) Deutsche Telekom Service Europa build a centre of excellence unit that supports IT and Business alignment and support for process mining software. (Lillig, 2020) The next chapter will study organizations, governance models as part of the operational model.

5.7 Performance Management, Monitoring and Continuous Improvement

As concluded in chapter three, process mining provided monitoring of process as a direct benefit and business benefit as an indirect benefit when the companies take further actions. Eventually, the organizations decide how to integrate process mining into their organizations, but as many studies show, process mining should be implemented in actionable and repeatable manners to gain business benefits continuously.

As seen in chapter three, many process mining service providers offer process monitoring and many use cases target monitoring their processes and improving the performance of their process. Top of monitoring the processes themselves, monitoring and measuring changes is essential after implementing process mining and taking actions. The companies need to define key performance indicators (KPIs) to judge if the efforts are successful. Moreover, if needed, take more actions to optimize their processes. (Van Der Aalst, 2016) Process mining can support continuous improvement programs by monitoring the processes and having quality and compliance controls continuously by using process mining. (Van Der Aalst, W.M., 2020)

5.8 Change Management, Culture and Mindset

As discussed earlier, process mining provides transparency on the processes and the data. Also, optimizing and improving the processes requires changes on processes, ways of working, or maybe even in the organizations. Initially, the companies may face setbacks and resistances while introducing and implementing the process mining as in many change management initiatives. (Buhrmann, 2020) It is recommended to define efficient change management in the early stage of process mining initiatives. (Schukat, 2020)

5.9 Result And Conclusion

This chapter presented many factors that may impact process mining implementations and requirements to succeed with process mining. One of the critical factors is identified as data readiness and management. The companies need to identify IT systems that can provide the needed data for the processes and develop a model to manage the data. Furthermore, continue with process mining, analysis and improvements.

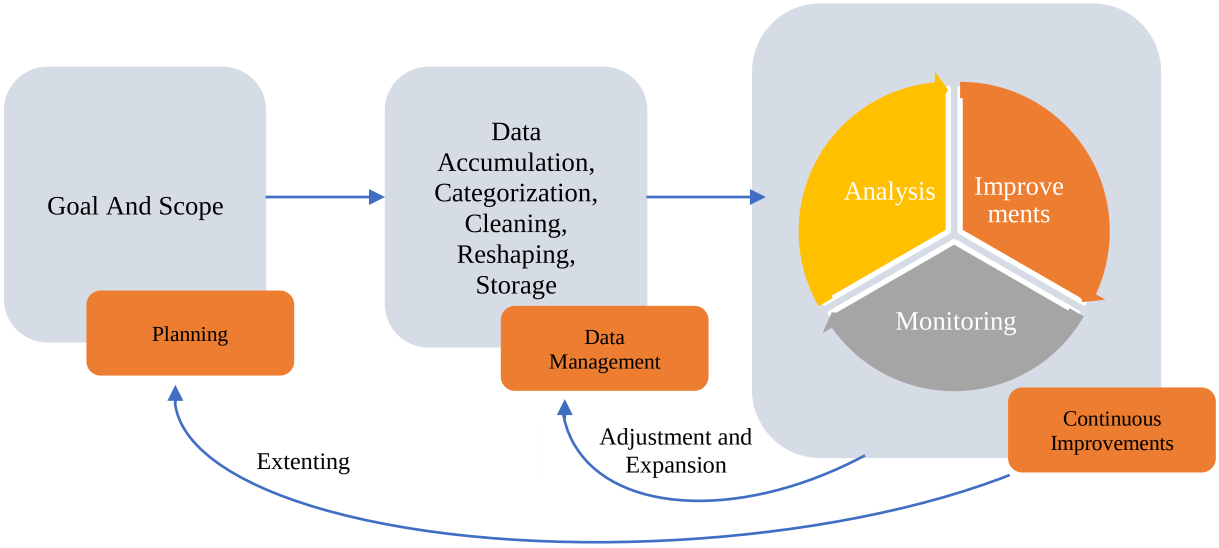

Figure 25 Process Mining Implementation

The chapter also discusses how other factors impact process mining implementations, the best practices, and lessons learnt. Based on the discussions and findings, it is recommended to start in small scale project on a process that the benefits are proven. Then the companies can define their approach how they will continue using process mining, set targets and develop the technology landscape. In addition to technological readiness and preparations, the companies need to develop a governance model, define organizational structure.

Eventually, extend process mining as part of continuous improvement culture enterprise-wise. Figure 26 presents the conclusion of how companies can start, and scale process mining based on different practices and lessons learnt from different sectors and industries.

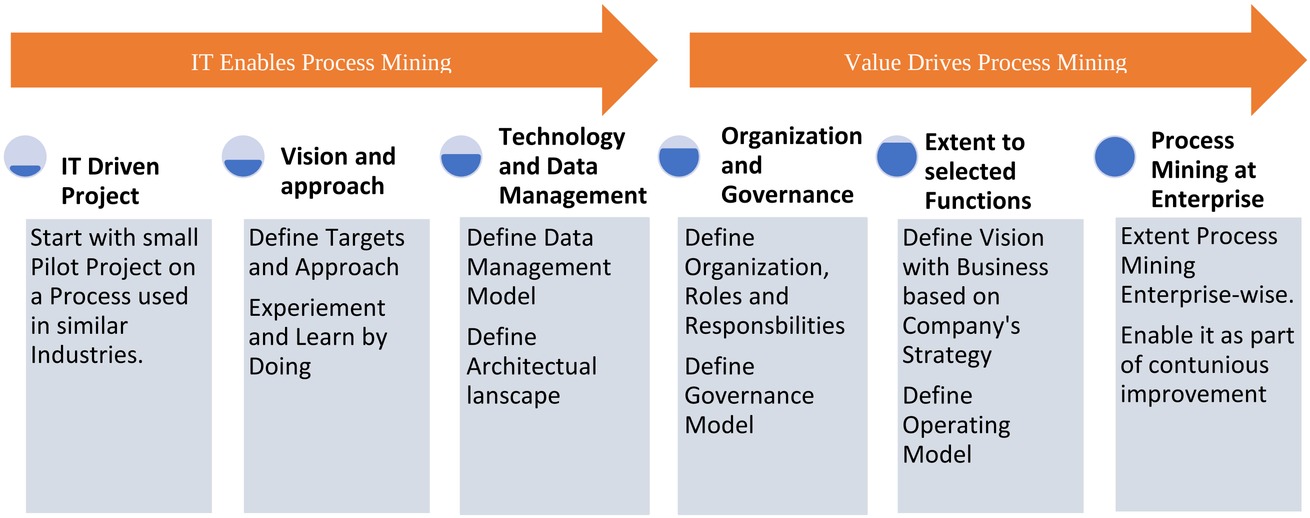

Figure 26 Process Mining Implementation: from project to enterprise-wise

6 RESULT: TARGET OPERATING MODEL

The operating model is defined as “a visual representation in the form diagrams, maps, tables and charts that shows elements of an organization such as activities, decision processes, information systems, etc. that are important for delivering the organization value propositions and how elements are combined to deliver the value propositions successfully.”. (Campbell, Gutierrez, and Lancelott, 2017) There are many interpretations thus many elements included in the framework by different parties. Campbell et al. describe the elements of the operating model canvas as value chain, organizations, locations, information, suppliers and management system. (Campbell, Gutierrez, and Lancelott, 2017). Deloitte describes the process mining operating model elements as an organization, people and skills, roles and responsibilities, IT Integrations, Processes and Controls, and governance. (Galic and Wolf, 2021). Despite minor differences between definitions and frameworks, all concerns deliver value and cover processes, people, organizational structure, information systems, and more. (Campbell, Gutierrez, and Lancelott, 2017).

Campbell’s Operating Model Canvas states that an operating model needs to be developed when companies are introducing something new, changing the strategy, having performance problems, teams are not aligned, implementing significant change (Campbell, Gutierrez, and Lancelott, 2017). It is realized that the companies who implement an operating model reported greater strategic effectiveness, higher operational efficiencies, more customer intimacy, higher product leadership and greater strategic agility (Ross, Weill, and Robertson, 2006).

According to chapter three, process mining is applied in various use cases such as transformation, process improvement, automation and more. These cases may bring a significant change in the companies and may result from a change in the strategy. In fact, it is suggested that companies establish a data-to-value strategy while implementing process mining enterprise-wise. (Galic and Wolf, 2021). As discussed, for strategic transformation to succeed, the companies need to define how they create value, an operation model aligned with the strategy (Kwan, Schroeck and Kawamura, 2018).

This chapter focuses on creating a high-level operating model for companies taking the knowledge gained from chapters two, three and four into consideration.

6.1 Why does Process Mining need an operating model?

Based on the study's findings, it is understood that **process mining is not a one-time activity**; the companies may benefit from discovering conforming or monitoring the processes, but improving the processes requires a continuous improvement roadmap. The cases we studied, QPR, ABB, Siemens Healthineers, Minit, presented that business benefits are realized when the companies start to have full transparency, improved real-time analysis, better monitoring opportunities. Furthermore, they needed to take improvement activities continuously based on discoveries; the process mining projects were not one-time activities. (Chapter 3.2) Process Mining Manifesto also states the same as part of guiding principles:

“Processes change while they are being analyzed. Given the dynamic nature of processes, it is not advisable to see process mining as a one-time activity. The goal should not be to create a fixed model, but to breathe life into process models so that users and analysts are encouraged to look at them on a daily basis.” (Process Mining Manifesto, 2012)

It is essential to highlight that a big part of process mining implementation is preparing the data. It requires multiple activities, diverse expertise, and continuous **data management and governance**. (Chapter 4.2) Moreover, it is important to be able to reuse the prepared (chapter 4.6) and ensure data is managed responsibly while considering privacy and security. (Chapter 4.3.2)

Process Mining implementation also requires internal or external **people** with various **skills** and **responsibilities** (Chapter 4.4.), a proper **technological** landscape (Chapter 4.5), change management and governance bodies (Chapter 4.6 and 4.8) in order to prioritize different use cases by business value, alignment of **strategy** and vision. They need to bring IT and business competencies together. (Galic and Wolf, 2021)

To add value aligned with their strategies and visions, the companies need to define “what needs to be done, where the work gets done, who does the work, how to drive better outcomes?" (Kwan, Schroeck and Kawamura, 2018). Having a clear vision and way of working helps them tackle the challenges related to technology, data management, and resources. Many companies that underwent such transformations (e.g., agile transformation) modified their organizations to be more value-oriented, improved collaboration between IT and business, redefined the role and responsibilities, and reconsidered their budgeting and planning models. (Comella-Dorda, Lohiya and Speksnijder, 2016) Defining a clear operating model helps companies implement process mining in an actionable and repeatable manner. It helps avoid uncoordinated efforts within siloes and improve continuously aligned with their strategy and vision.

6.2 Elements of the Operating Model

Based on the findings, this paper suggests seven elements for high-level process mining: organization and Governance, Capabilities, Roles And Responsibilities, Processes and Controls, Technology, Data Management, Sourcing, People, Culture and Skills.

Figure 27 Elements of Process Mining Operating Model (designed by presentationgo.com)

6.2.1 Organization and Governance

Traditionally companies set their organizations demand-supply based with separated IT and business. In recent years, the development of agility is changing companies toward value delivery based and integrating IT and the business. (Coolen et al., 2018) The companies alter their organisational structures to have more stable teams with dedicated resources and end-to-end perspectives. (Comella-Dorda, Lohiya and Speksnijder, 2016)

As seen in the study process mining requires -at least- close collaboration between IT and business, different experts from different functions and this probably requires redesigning organizations for the company as seen in use cases shared. For example, BMW built the Centre of Excellence (CoE) unit responsible for building internal IT and Data competencies and built a process mining network to implement the process mining technology. BMW also underwent an agile transformation and designed a governance model to drive the business transformation with the support of CoE. (Reinmeyeker. 2020) to create clarity on the roles and responsibilities, create continuous improvement culture. (Jansen, 2020) Telecom Deutsche utilized CoE to steer project mining projects and used shared services for end-user support requests. (Lillig, 2020). It is concluded that It is essential to have a suitable governance model and organizations to have the right roles, responsibilities, and decision-making to succeed in implementing process mining. (Coolen et al., 2018)

The companies need an organization that can support the use of process mining and governance that serve the organization in alignment with the strategy and the vision.

6.2.2 Capabilities, Processes and Controls

Deloitte suggested that capabilities be configured in four different ways based on the type of value generated. (Kwan, Schroeck and Kawamura, 2018)

1. Shared capabilities that scale across products, geographies, customer segments.
2. Steering Capabilities that are knowledge-intensive hubs sets the direction and enable strategy. (Decision making)
3. Specialist capabilities responsible for decision making and critical thinking tasks require specific expertise.
4. Support Capabilities support operational excellence.

The companies implementing process mining enterprise-wide need to allocate these capabilities to define roles and responsibilities. Based on studies in this paper, it can be suggested that the companies can utilize capabilities as:

1. Process Mining team that is responsible for implementing process mining across organizations. The team consist of experts and practitioners of process mining
2. Steering community who can decide quickly based on the company's strategy can prioritize uses cases according to business value and other aspects based on the company's priority matrix.
3. Process and data expert that understand the processes and data to support initiatives
4. Support or service team that support end-users, companies can utilize their existing service management.

The companies need to define workflows, demand and development management, support processes for implementing process mining, and workflows related to compliance, audit procedures, KPI. (Galic and Wolf, 2021) Also, processes and controls define how different capabilities will work together.

6.2.3 Technology

Technology is essential to drive and support process mining initiatives, projects, and programs. The companies need to define a long-term process mining technology strategy. (Galic and Wolf, 2021) As discussed in chapter 4.5, process mining requires a technology landscape where companies design architecture to integrate multiple systems to gather data, have platforms to manage data. In addition to that, the companies need to define how to create an eco-system where they can integrate various technologies such as business analytics systems (e.g., Qlik), RPA Solutions, other mining, AI and machine learning solutions. This paper suggests that companies focus on technology with a team that follows new technology and innovation trends and adopts new technologies to ensure the full benefit of process mining and any technology that could add value.

6.2.4 Data Management

The previous chapter discusses the importance of data and data management. (e.g., Chapter 4.3). Based on the findings, this paper suggests that centralized data management and long-term data strategy are essential success factors for process mining initiatives.

6.2.5 Sourcing

As discussed in previous chapters, process mining requires many internal or external experts. The availability of these experts is one of the success factors of process mining initiatives. (Galic and Wolf, 2021). It is essential how companies manage relationships with partners and ensure collaboration between internal and external resources. As in the use cases, the companies mostly need consultants from service providers related to software or process improvement knowledge and experience and software or tools.

The companies may need to consider having the sourcing organization separately to work on selecting the right partners with collaboration other parties, negotiating contracts, managing relationships also supporting operational costs such as licenses. If the company uses process mining globally, defining how responsibilities are shared between local and global functions may be essential. (Barillà et al., 2015)

6.2.6 People, Culture

Process mining implementation may change the companies as it increases transparency and identifies improvement opportunities. In addition to this, implementing a new operating model may cause organizational resistance and misaligned vision. (Kwan, Schroeck and Kawamura, 2018) People may not want to change way of working, or they may lack skills and knowledge. Companies can benefit from having a long-term people strategy, training and development management for skills required for process mining. (Galic and Wolf, 2021) Nominating and empowering people or units to drive cultural change, creating incentives and goals can reduce conflict (Kwan, Schroeck and Kawamura, 2018) and motivate people to change.

6.3 Operating Model

The high-level process mining operating model illustrates how a business value can be created. The target is to demonstrate how companies can manage demand on process mining, development and service while monitoring to ensure continuous improvement.

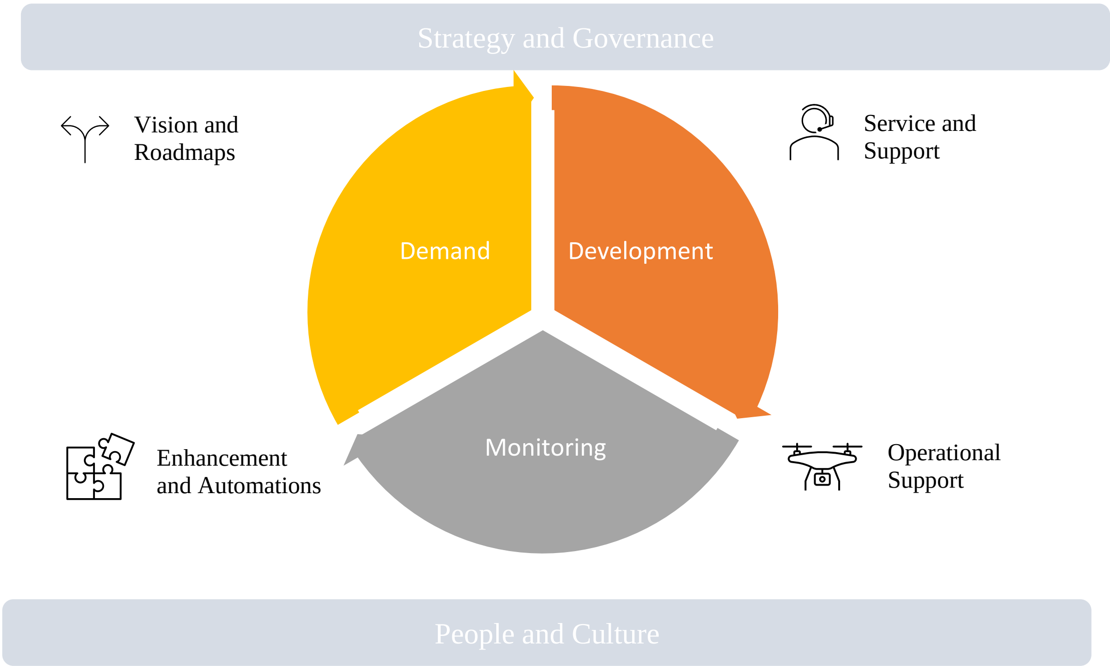

Figure 28 Target Operating Model

Demand Management is described as “receiving, evaluating and deciding upon work requests” (Deloitte, 2015). It starts receiving new ideas and changes requests and priorities them based on the matrix used for the prioritization. Demand management varies based on different methodologies (Waterfall, SAFe etc.) and frameworks. If SAFe is used as a reference, companies need to manage epics that are significant solution development initiatives (SAFe, 2021). They also need to manage ideas, change requests, and enhancement requests as backlogs that are “emerged, ordered list what needed to improve” (Scrum Guide 2021). The epics are new initiatives, for example, applying process mining in new processes or a significant automation initiative requested based on insights gained from process mining activities. Backlog items identified based on insights gained implemented process mining; discovery, conformance checking, enhancement, or operational support. The governance bodies should make decisions related to epics with the alignment of strategy and vision, whereas empowered solution teams can drive backlog items.

Development is the phase where the work request is implemented. Based on insights from previous chapters, it is suggested that discovery and conformance checking can be the first development target. Based on the insights, there can be more requests continuously. Once the process mining is implemented, it should be monitored to enable continuous improvement.

As mentioned, process mining requires the involvement of different people and a culture that supports transparency and continuous improvement. Therefore, people need to be supported with a mechanism to support their daily routines (access and incident management) and learning opportunities to use the new tools, solutions, change management, lean and agile.

7 DISCUSSION AND CONCLUSION

The research focused on understanding why and how process mining is implemented so far and how the companies can operate to add value to their businesses. As the initial step, the paper focused on the theoretical background of process mining to understand what it is, where it stands in the scientific eco-system, and it continued with research questions.

What value can mining bring to organisations?

Process mining is placed between data and process sciences and consists of process discovery, conformance checking, enhancement. Furthermore, it can be combined with other fields or services to be used for monitoring, task automation and operational support. At this point, the paper focused on understanding the value process mining can bring to a company by identifying direct and indirect benefits and use-case examples for process discovery, conformance checking, enhancement, task automation. The research identified many cases with transparency, improving their processes, generating savings, reducing operating times, improving efficiency and productivity, automating tasks, and taking actions based on conformance and performance diagnosis to address the identified problems. However, the research could not identify any existing case where process mining can support run-time support: detect, predict, and recommendation except few proof-of-concept studies shared in the HSPI Process Mining Application Database. Therefore, the paper supports statements that indicate business value gained based on process discovery, conformance checking, monitoring, and automation. It strongly supports the statements related to the potential of run time operating support of process mining.

What are the best practices and lessons learnt established so far in different industries and sectors?

After understanding different business cases, and benefits gained, the paper focused on how these companies implement process mining and what they learnt. The research analyzed industries, sectors, use cases and adaption of process mining and how they are adopted and implemented. As process mining is a relatively new discipline and not implemented by many companies, limited information and knowledge were shared. Secondly, share use cases were mainly focusing on successful initiatives and practices. Therefore, the study relied on a limited number of use cases and advice shared by service providers. Considering these factors, the paper provided seven points to focus on while implementing process mining: 1. Vision and goals, 2. Data Management, 3. People, Roles and Responsibilities, 4. Software Services and Technology, 5. Organization and Governance Model, 6. Performance Management Monitoring and Continuous Improvement, 7. Change Management, Culture and Mindset. In addition to the focus areas, the paper also provided a high-level framework on how to start as an IT-enabled project to value-driven process mining.

What would work as an operating model for process mining?

After clarifying value delivered with process mining and knowledge related to lesson learnt on implementation, the paper produces elements of an operating model and a visual representation of high-level activities. The paper identified elements of the operating model as 1-Organization and Governance, 2. Capabilities, Processes and Controls, 3. Technology, 4. Data Management, 5. Sourcing, 6. People and Culture. The paper also produced high-level activities as demand development and continuous monitoring, which generates enhancement and automation requests and prediction and recommendation for operational supports. The study also highlights alignment of strategy and vision in demand management, the importance of people and culture initiatives and activities in the organization and end-user support.

The research concludes that the process mining implementation is not about software or new technology only. It requires an operating model that to support the vision. It requires additional competencies, clear roles and responsibility definitions, attention to architecture and data management. It is a significant transformation; therefore, it is in companies’ best interest to find the right approach for the transformation that requires leaders' commitment.

The best way to gain value from process mining is through experience and failing fast. The companies need to be open to change, experiment, fail and take actions accordingly. It is also implemented process mining iteratively, starting with simple processes, areas where they can have quick results and where people are passionate about the changes.

An operating model includes decision processes; however, this study was limited to producing activities and elements only for an operating model. The decision processes are linked strongly with the company's methodology or framework. This paper did not study how the process mining operating model can be aligned with different methodologies and frameworks. Future studies could focus various subjects around methodologies and frameworks that may be used by companies such as:

1. Identifying the most suitable methodologies and frameworks for process mining and defining decision processes.
2. Adapting process mining in a company where a methodology or framework is used (such as agile, waterfall, SAFe etc.)

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