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Process Mining the Requisition-to-Pay Process

Utilising QPR ProcessAnalyzer in Wärtsilä's Indirect Procurement Department

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Thesis abstract

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Process mining is on trend as organisations aim to make their operational processes more efficient. To do so, companies need a clear understanding of current processes. Research shows that people tend to be aware of 40% of a process, and reality is far more complex and inconceivable due to variations, this is where data-driven flows can create valuable insight. Complete overviews of processes can be analysed via algorithms. Thus, outlining business priorities, allowing flow simulation and automation opportunities for further progress.

The purpose of this research was to examine how process mining, more specifically QPR's ProcessAnalyzer, can be utilised and applied to a procurement function. The goal was to analyse Wärtsilä's Indirect Procurement Requisition-to-Pay (R2P) process, pinpoint its inefficiencies and bottlenecks, test development project ideas and key performance indicators (KPI) with real-time data, to enhance business case proposals and bring these findings to management, thus being able to prioritise developments in the correct areas.

This thesis reports methods for applying a process mining project in a business. The overall background, process mining steps and purposes, its benefits and challenges, as well as the project team's experiences and lessons learned are presented. As well as practical information regarding insights into the process, how to identify bottlenecks, inefficiencies, and areas for improvement. Thus, basing informed decisions on real-time data, to streamline the process.

The research results confirm that process mining is a valuable tool to support developments and process improvements, already displaying a return on investment. However, it is important to create professional dashboards to present findings to management, and it is advised to have a proactive process mining representative to enhance the success of the endeavour. Though process mining has extensive potential, technology alone is not adequate, the role of process experts is significant in data transformation, validation and in drawing conclusions. Further collaboration with other teams and focusing on end-to-end continuous improvement could be a positive next step.

Keywords: Process Mining, Process Discovery, Optimising Business Processes, Requisition-to-Pay

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Terms and Abbreviations

IP	Indirect Procurement
R2P	Requisition-to-Pay
P2P	Purchase-to-pay / Procure-to-Pay
PO	Purchase Order
PR	Purchase Requisition / Req
ERP	Enterprise Resource Planning
SRM	Supplier Relationship Management
BPM	Business Process Model
BPMN	Business Process Model Notation
ID	Identification
ETL	Extract, Transform, Load
SQL	Structured Query Language
KPI	Key Performance Indicators
PPI	Process Performance Indicators
SLA	Service Level Agreement
E2E	End-to-End
RPA	Robotic Process Automation
AI	Artificial Intelligence
ROI	Return on Investment

1 INTRODUCTION

Large companies utilise Enterprise Resource Planning (ERP) systems to help run their entire business operations, as these systems help manage business functions across companies whilst focusing on heavy data storage in a shared database. There are ample modules including accounting, customer relationship management, human resources, manufacturing, marketing, project management, quality assurance, sales, and supply chain within ERP systems.

Cavintek (2023) states process inefficiencies tend to negatively impact companies in terms of customer engagement, workforce contentment, mistakes, re-work, neglecting work, waste of resources, amplified operating costs, holdups, and bottlenecks. Thus, it would be an oversight for a company not to improve and develop their processes within existing ERP systems. To do this, companies should have a clear understanding of their current business processes.

According to Schmeizer and Walch (2022), there are plenty of platforms on the market which businesses can utilise for process optimisation. In the mid-1980s Six Sigma and Lean thinking were adopted, Total Quality Management (TQM) was also used by manufacturers and government agencies. Wyatt (2018) elaborates that there has since been a multitude of middleware developed. Business Process Management (BPM) software entered the market in the 2000s, however, this focuses on specific processes and optimises them to their full potential, instead of managing and storing data as an ERP system, according to Hayes (n.d.).

Bartley (2020) states 90% of the world's data was created between 2018–2020 and every two years the volume doubles. Van der Aalst (2016, pp. 3–10) claims that such a rapid expansion of data is often referred to as "Big Data". This provides an opportunity to obtain and analyse events when information is inserted into information systems, social networks, machines, etc. Available data is known as Internet of Events (IoE) which spans content, people, things, and locations.

> "Process mining aims to exploit event data in a meaningful way, for example, to provide insights, identify bottlenecks, anticipate problems, record policy violations, recommend countermeasures, and streamline processes. This explains our focus on event data." (van der Aalst, 2016, p. 5)

As most data is unstructured, companies have struggles handling its multitude, especially when attempting to obtain value from it. Hence, this is where process mining can be used to support and create value to organisations (van der Aalst, 2016, p. 10).

As an example, the process of a teenager making a trip to a city and visit a museum is illustrated by van der Aalst (2016, p. 8–9). There were many steps in this process such as exploring online, finding what trains were available and the ticket prices. Checking the schedules and opening times of the museum and sharing this information with friends. Going on the train and using a card to pay for the ticket. The train being subject to a delay which the teenager complained about on social media, thus getting a refund. Then deciding to go to the museum via a bus, paying for the tickets and going home. There were many events (steps) in this process, some are clear to understand where logs occur. However, some events are harder to relate to and may not occur for others or contain data, this complicates an analysis. Thus, why event correlation is a foremost dilemma in data science.

However, data science is not limited to Big Data, the data itself is rapidly shifting which poses difficulties, according to van der Aalst (2016, p. 9–10). There seems to be a unity in its key attributes, including volume, velocity, variety, and veracity. Further, to clarify, data science is the act of extracting information and knowledge from data (Provast & Fawcett, 2013). This definition is elaborated on by van der Aalst (2016, Chapter 1.2) stating that data science aims to drive data into real value, it can be grouped into four categories: reporting, diagnosis, prediction, and recommendation. The interjecting components span over: statistics, privacy, security, law and ethics, behavioural and social science, business models and marketing, visualisation and visual analytics, distributed systems, databases, predictive analytics, process mining, machine learning, data mining, and algorithms.

Process science, on the other hand, is the wider discipline of knowledge from IT and management science to improve and run operational processes, one of its key concepts is business process management (BPM). Process science focuses on the models and process mining focuses on the insights from the data (van der Aalst 2016, pp. 17–21). Further, Arunachalam (2018, 35) states business analytics is the exercise and ability of utilising quantitative data to support decision making. As well as data-driven decision-making in SCM is crucial (op. cit., p. 294). In today’s business word, a level up from analytics is business intelligence (BI) which uses data visualisation and reporting to attain awareness and understanding of what the data is and what has occurred within the data. However, according to O'Carroll (2020), it is important not to get business intelligence (BI) and process mining confused. BI focuses on high-level measurements such as KPIs, and trends which pose queries on the process(es) attaining productivity criteria or specific client demands.

Lehto (2020, p. 104) illustrates that the simplified version of a process is referred to as a text-book version, this tells ~20% of the process. However, what people commonly think the process is, and often display it as, covers ~40% of the process. The reality of the process, i.e. 100%, is the complex and unmanageable data-driven flow which is only possible to see via process mining. Espinosa-Leal et al. (2020) suggest it is becoming increasingly important to query and analyse current processes, to discover inefficiencies, bottlenecks, and root causes. This is not only due to resource related reasons, but also to generate automation, objective and instant information which can continue to predict and learn from data (op. cit.). Thus, increasing ROI and guiding businesses to focus in the correct areas, increasing performance.

Traditionally organisations have focused on where they would like their process(es) to be but have not been able to obtain true data on where they are now (Badakhshan et al., 2022, p. 3). This is possible with process mining. Thus, allowing companies to adapt processes and take advantage of improvements. Further, providing insight into development areas such as process automation. It is key to note that although robotic process automations (RPAs) are on trend, it is first vital to optimise the current workflow/process, i.e., reducing the steps and cutting out the unnecessary portions of the process (op. cit., pp. 8, 12–13). The reason for this is making a process lean and simplified before automating it, thus ensuring upmost efficiency.

Lacy-Hulbert (2022) claims process mining has evolved in recent years and is likely to continue as technologies develop. Kermani et al (2024, pp. 134342, 134353) write process mining is on trend, especially in project orientated companies as they are recognising its necessity to remain viable and provide them a with a competitive advantage. Badakhshan et al. (2022, pp. 1–2) confer this trend and that there is an increasing interest in process mining research and practice, although they state it is unclear how organisations use process mining to create value.

This thesis has used the WärtsiläGPT language model for text summarisation. All sources used in this thesis were retrieved by the author, not sources generated by AI. Where AI has generated text, it has been checked against the original sources, and properly referenced.

1.1 Research Aim

Analysing the Requisition-to-Pay (R2P) process, in Wärtsilä's Indirect Procurement department, via process mining aims to identify process issues and provide invaluable insight into the system data. This can be utilised for identifying areas of lean-process advancements and automation opportunities. According to Zerbino et al. (2021, p. 11), procurement may see process mining as an innovative method for business insights in the near future, as data is expanding, and digitalised platforms advance in support and accessibility for process mining efforts to be attainable. However, there is a lack in research at present with regards to the procurement process and process mining.

In terms of added value, this thesis will also offer more in-depth experience with project management and process development which is useful to the authors' expertise. This project demonstrates how development projects can be achieved whilst reporting on the process and offering answers to the research questions. Furthermore, providing solutions to other experts in their fields, as well as companies, that have likely struggled with similar issues and are in the process of considering comparable process mining solutions.

Applying process mining in business operations can pose obstacles, however, these are not the focus of this study, although they will be briefly considered. Instead, the focus is to consider how process mining can be utilised and what techniques can ensure successful implementation. Steps will be considered in the literature review and commence into the project. As per project management deliverables, outcomes and findings will be presented too.

Thus, the two main research questions are:

1. How can the QPR ProcessAnalyzer tool be utilised in the R2P process?
2. What techniques are required to ensure process mining is successful?

The introduction part of this study covered the background, objective, the research problem, and research questions, as well as the case company information, and service provider overview relevant to the project.

2 THEORETICAL STUDY

The theoretical part of this study will introduce the process mining concept in theory, and the service provider's platform chosen for this endeavour, along with its capabilities. To conclude, the development analysis will be drawn up based on the theoretical findings and utilised to draw up a plan of action for the empirical study.

2.1 Process Mining

Van der Aalst (2016, pp. 20–21) emphasises process mining research began in 1999. Since then, data has become freely available and practices used in process mining have matured, and algorithms have been executed in academic settings as well as business systems. Today, it has become a hot topic in business process management as well as seen a swift interest in industries. There is also an open-source platform available which has helped gain momentum, however, there is minimal literature on process mining. Most scientific articles, online articles, and blogs, reference van der Aalst in their publications as there are limited books available.

Van der Aalst (2016, p. 17, 25, 31, 32, 448) expresses there has been a chasm between companies' operational processes and IT systems' data, the objective of process mining is to bridge this gap. Process mining commences with event data and projects these to process models for discovery, as a reference, see Figure 1. Data-driven and process-centric forces are harmonised, unified, and codependent. It is possible to answer performance and conformance questions as the combination of event data and process models provide intel on activities and dependencies.

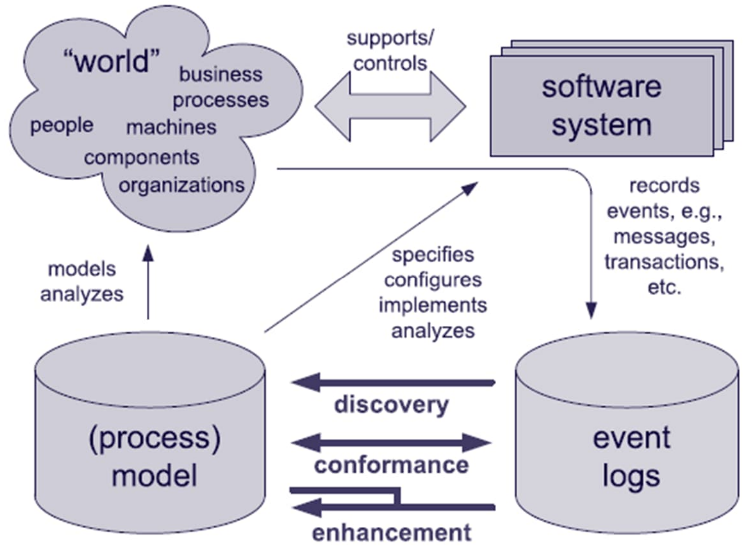

Figure 1. Three main forms of process mining (van der Aalst, 2016, p. 32).

The three main forms of process mining, according to van der Aalst (2016, Chapter 2.2), include discovery, conformance, and enhancement. Their positions sit between event logs and the process model. Discoveries can be made from the event logs which populate the process model without prior information. Conformance analysis compares an existing process model with an event log in the same process, which can be useful when considering if process directives have been followed. The conformance analysis can uncover, pinpoint, and clarify deviations as well as measure their severity. Enhancements' role in process mining is to improve a model using data recorded in the event log. The aim is to change or extend the current process model, either to repair the current process model to reflect reality from the event data, or to expand a new perspective by drawing parallel to the event log. This can therefore show bottlenecks, levels of service provided, handling times, and quantities in a process. The enhancement portion can also include metrics of performance.

QPR (n.d.-b) stipulates that process mining combines business process management and data mining, hence, it is a data-driven approach to mining. Utilising business processes with timestamps, case identifiers and event types are mandatory, as data is required to generate outputs. Once the data is collected from information systems it is used to visualise the real-life execution of the companies' processes. Figure 2 illustrates a simplified R2P process where each "case" goes through various "event" timestamps, and the data is stored in; SRM, ERP, and Finance databases. Each company may structure its data storage differently, below is an example of this process.

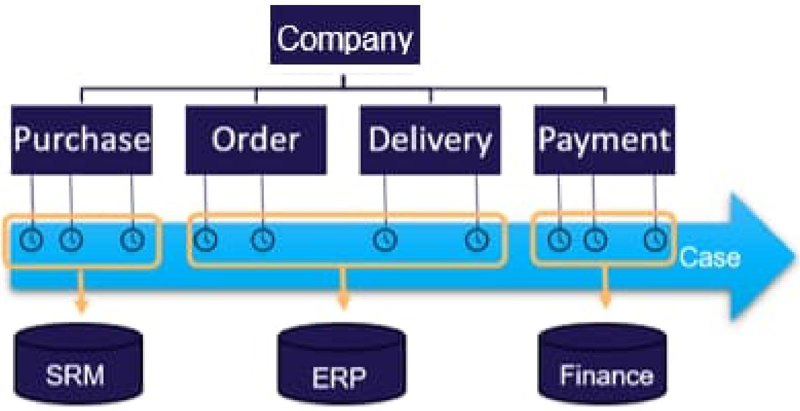

Figure 2. R2P Process: Case example (QPR, n.d.-b).

As QPR (n.d.-c) asserts, the process mining concept enhances opportunities in locating bottlenecks, and issues in processes such as time-consuming areas from core data. Therefore, providing new insights on fact-based information which can be used for decision making. The latest capabilities of process mining also generate best suggestions on next steps to take or allow a bot activation to execute manual tasks (op. cit.).

2.1.1 Steps of Process Mining

According to van der Aalst (2016, pp. 125–127) process mining cannot occur until after extracting, transforming, and loading data from sources *(otherwise known as ETL),* as displayed in Figure 3. It is said to be common that sources are scattered, and the collection process may be cumbersome since e.g., SAP data alone can have more than 10,000 data tables. As van der Aalst also states many organisations scatter the data to control access, e.g., across functions and departments, it is also common to archive legacy data. The complexity of data varies from organisation. The data extraction can also come from external sources. Transformation of the data is done per operational requirement, and the loading is completed by choosing the destination of the data e.g., a data warehouse. If a data warehouse is used, then it could later be revisited to obtain the repository. However, a data warehouse does not produce data, it merely utilises data from operational systems and aims to bring the data together.

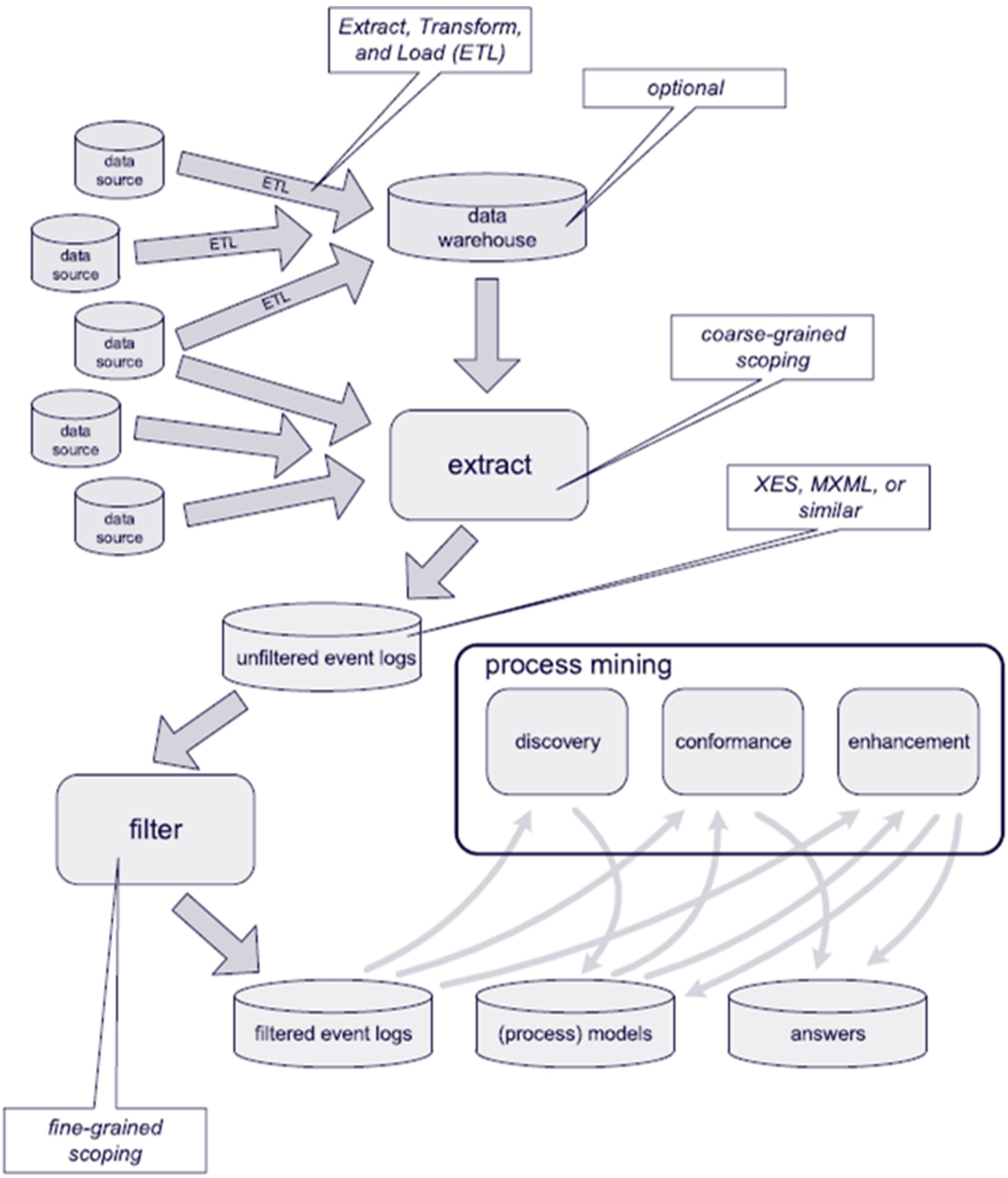

Figure 3. The Steps in Obtaining Data from Diverse Sources to Gain Results (van der Aalst, 2016, p. 126).

Van der Aalst (2016, pp. 415–416) describes that once event logs have been filtered the following four methods can be followed to gain answers:

3. Filtered event logs -> discovery -> process models -> conformance -> answers.
4. Filtered event logs -> conformance -> answers.
5. Filtered event logs -> enhancement -> answers.

6. Filtered event logs -> discovery -> process models -> enhancement -> answers.

According to QPR (n.d.-c) there are 7 steps of process mining, these are outlined in Figure 4. Including collecting data, preprocessing data, discovering processes, analysing, and drilling down on root-causes, optimising processes, obtaining automation candidates for prioritisation, and predicting KPI performance and preventing problems.

Collect data

Data is collected from event logs, generated by systems such as ERP, BPMS, CRM, HR, ITSM, etc. Process mining tools take the existing transaction data from these information systems with pre-built connectors. QPR help their clients get set up.

Preprocess data

Data is often preprocessed (cleaned, removing inconsistencies, and sometimes transforming ithe format). QPR experts do this work for their clients.

Discover processes

Use the software to discover the real-life process from the data. Clients will see automatic visualisations of their as-is process flows and discover how their processes perform. Drill down to details, or take a high level view.

Analyse and drill down on root-causes

Clients can analyse the process using various process mining metrics and techniques e.g. measuring performance indicators such as lead time, conformance, or process efficiency, and identifying areas where the process can be improved. The Root Cause Analysis reveals the reasons behind the problems in cleint's processes (e.g. bottlenecks, rework, and unwanted process variations).

Optimise processes

Clients can start improving processes via improvement methodologies. By optimising processes, clients can improve performance, reduce costs, and increase efficiency.

See automation candidates for prioritisation

Shows which processes are suitable for automation – in priority. View expected ROI, automate where it makes sense, and easily scale automation initiatives.

Predict KPI performance and preventing problems

Keep monitoring and predicting KPIs and measure how strategic objectives are met with process mining. Process mining gives instant, dynamic reports.

Figure 4. The Seven Steps of Process Mining (QPR, n.d.-c).

Thus, QPR appear to be supportive in the beginning on the process where data collection and preprocessing of data is involved. There are also trainings available for the practicalities of how to utilise the tool itself and the clients are expected to learn the methods themselves, although it is possible to gain support from QPR, nonetheless. The above steps outline that van der Aalst's four methods in terms of QPR's capabilities are Filtered event logs -> discovery -> process models -> conformance and/or enhancement -> answers, i.e., concerning options 1 and 4.

2.1.2 Process Models

Van der Aalst (2016, Chapter 15) states that process models gain insight into a specific process. A process model allows stakeholders to discuss the content, they are required for instructing people and can provide documentation. They also tend to be used to verify/locate errors in systems or processes, and to understand influencing factors within the process such as response times, level of service, etc. Process models are said to provide a means to produce scenarios and give feedback to the creator of the model, as well as serve as an agreement between developers and clients. They can also be used to re-shape platforms as they give an overall view of steps.

Van der Aalst (2016, pp. 29–30) describes that there are two types of process models, informal and formal. Informal process models are discussed and documented; they are often high-level overviews of the process. Whereas formal process models are used in practice and often for performing analyses, they include an in-depth drill down of detailed steps often including technical data and codes. Unfortunately, research has identified the lack of alignment between these types of process models, which have been designed by professional in the business.

According to van der Aalst (2016, 268), when changes to processes are being considered, business professionals often refer to the current process models in place. This is especially the case in larger organisations, who rely on such models to consult higher management, stakeholders, consultants, newcomers, and so on. Process models do not necessarily portray reality, nonetheless, they can still be useful and reflected upon. It is however important to ensure that the process models align with reality as much as possible, especially since there is great interest in these from stakeholders across larger organisations. Further, as research has identified limitations in self-designed models, it could be valuable to align process models with reality.

Van der Aalst (2016, p. 35, 431–432) states this is where process mining can prove invaluable, since it utilises real event data to discover the actual process at greater speed. It can also evaluate the data with existing models and consider improvements. Further, displaying models of the data and allowing users to choose to deep-dive into certain areas of the process, in a visual format. Automatically generated models are possible via process discovery algorithms such as the α-algorithm.

Van der Aalst (2016, p. 277) provides an example of the process model in relation to the event logs. Figure 5 provides an overview of case IDs 1 and 2, the breakdown of event IDs falling within each case ID, along with the event's properties such as timestamps, activity types, resource, and cost.

Case id	Event id	Properties				
		Timestamp	Activity	Resource	Cost	...
1	35654423	30-12-2010:11.02	register request	Pete	50	...
	35654424	31-12-2010:10.06	examine thoroughly	Sue	400	...
	35654425	05-01-2011:15.12	check ticket	Mike	100	...
	35654426	06-01-2011:11.18	decide	Sara	200	...
	35654427	07-01-2011:14.24	reject request	Pete	200	...
2	35654483	30-12-2010:11.32	register request	Mike	50	...
	35654485	30-12-2010:12.12	check ticket	Mike	100	...
	35654487	30-12-2010:14.16	examine casually	Pete	400	...
	35654488	05-01-2011:11.22	decide	Sara	200	...
	35654489	08-01-2011:12.05	pay compensation	Ellen	200	...

Figure 5. An Example of an Event Log (van der Aalst, 2016, p. 277).

Further, Figure 6 demonstrates a compact version of the above log data containing case IDs and traces of events, as per van der Aalst's (2016, p. 37) example. This is then transferred into the process model as represented in Figure 7,Figure 7. Compact Log Data and the Process Model Discovered by the A-Algorithm (van der Aalst, 2016, p.37). which labels the events as per activity types represented by a letter. For example, a= register request, b= examine casually, c= check ticket, e= decide, f= reinitiate request, g= pay, and h= reject request. Each activity type is displayed as per procedure connecting one activity to another in the process, including the process start and end.

Case id	Trace
1	$\langle a, b, d, e, h \rangle$
2	$\langle a, d, c, e, g \rangle$
3	$\langle a, c, d, e, f, b, d, e, g \rangle$
4	$\langle a, d, b, e, h \rangle$
5	$\langle a, c, d, e, f, d, c, e, f, c, d, e, h \rangle$
6	$\langle a, c, d, e, g \rangle$

Figure 6. A Compact Representation of the Event Log (van der Aalst, 2016, p. 37).

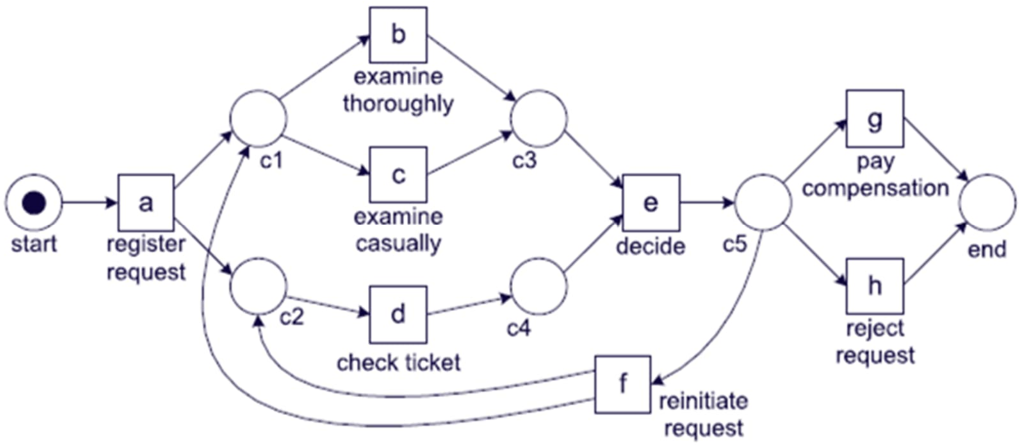

Figure 7. Compact Log Data and the Process Model Discovered by the A-Algorithm (van der Aalst, 2016, p.37).

Van der Aalst (2016, p. 85–88) highlights that business and process performance can be measured in various ways, the most common include time, cost, and quality. Often Key Performance Indicators (KPIs) are derived of these. Van der Aalst elaborates that most BPM tools provide simulation prospects. However, it tends to be time-consuming to feed data into these tools. As process models and reality do not tend to align, although that would be desirable, this means that model-based analysis does not seem practical. The same is said to apply for simulation models in BPM tools as the likelihood of flawed assumptions, which these models are based upon, are evident. Therefore, process mining would be ideal to assist businesses in their process improvements as its models would be built upon authentic event level data with the possibility to approach such data via alternate perspectives and levels of detail.

Algorithms are used in e.g. process discovery, and conformance. It is clear to see the process mining algorithm in action, in Figure 8. At the present time, the initial process model is presented. However, the predictions can be seen along the process, as events occur, and variables change, the process model changes whilst the event streams are updating. All events are stored in a database, and the algorithms can access the event data at any given time. This therefore allows questions from organisations to be answered in a timely manner.

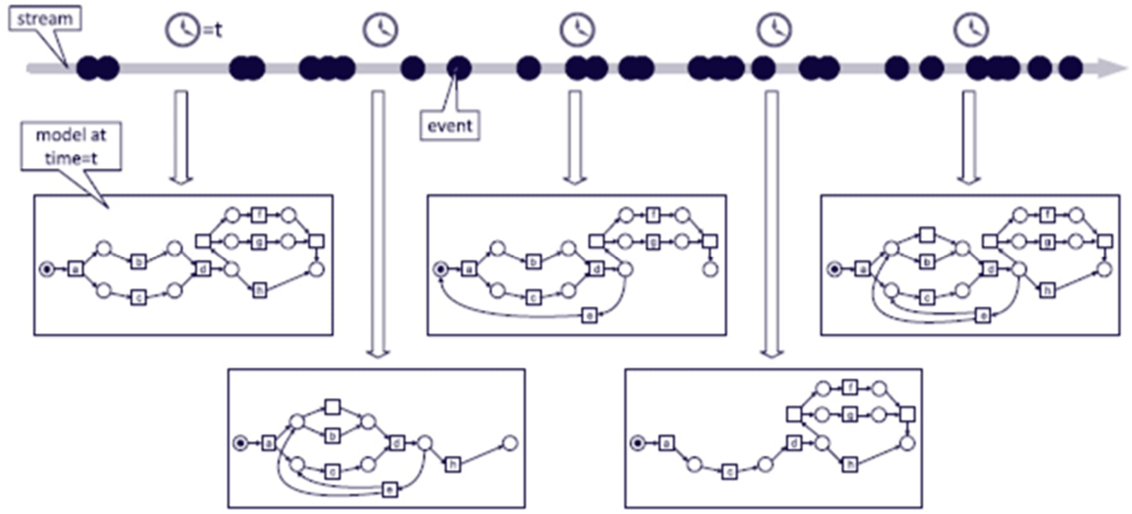

Figure 8. Up-to-date Process Models of Event Streams (van der Aalst, 2016, p. 382).

Although, van der Aalst (2016, p. 381) elaborates that it is not ideal to store all data continuously, but events can be archived and retrieved later, if required. Lastly, van der Aalst (2016, p. 13, 50) also outlines that process mining algorithms can also provide predictive analytics and intelligent services to provide insights and forecasts into processes.

2.1.3 Analysing Processes

Analysing business processes is one of the most important steps after data has been mined. According to van der Aalst (2016, p. 387–388) the terms “structured”, “semi-structured”, and “unstructured” are used to refer to processes. In a structured process all activities are repeatable and have well defined inputs and outputs. In principle, the activities in highly structured and processes can be automated. In semi-structured processes the information requirements of activities are known, and it is possible to outline the process. However, some activities require human judgment, and deviations occur depending on the characteristics of the case. Unstructured processes are the most difficult to define as they are claimed to be driven by experience, intuition, trial and error, rules of thumb, and vague qualitative information.

Van der Aalst (2016, Chapter 13) claims Lasagna processes have a clear structure, and most cases are handled in a prearranged manner. There are relatively few exceptions and stakeholders have a reasonable understanding of the flow. A process is considered a Lasagna process if it is possible to create an agreed model of at least 0.8, i.e., more than 80% of the events happen as planned and stakeholders confirm the validity of the model. Spaghetti processes are less structured, making only a subset of process mining techniques applicable. Further, process mining tools should be able to predict the remainder of the process flow in terms of time or recommend the action with the lowest costs. However, in spaghetti processes this would not be possible due to the vast variables involved. Nevertheless, process mining can still uncover key problems and lead to dramatic process improvements in spaghetti processes.

2.1.4 Process Mining Project Lifecycle

As outlined in Figure 9, a process mining project lifecycle is said to consist of five stages, according to van der Aalst (2016, Chapter 13.3). Planning and justifying (stage 0), extracting (stage 1), creating a control flow model, and connecting even logs (stage 2), creating integrated process models (stage 3), and operational support (stage 4). The lifecycle model applies to Spaghetti processes, in terms of stages 0, 1, and 2. However, creating an integrated process model (i.e. stage 3) is often not feasible.

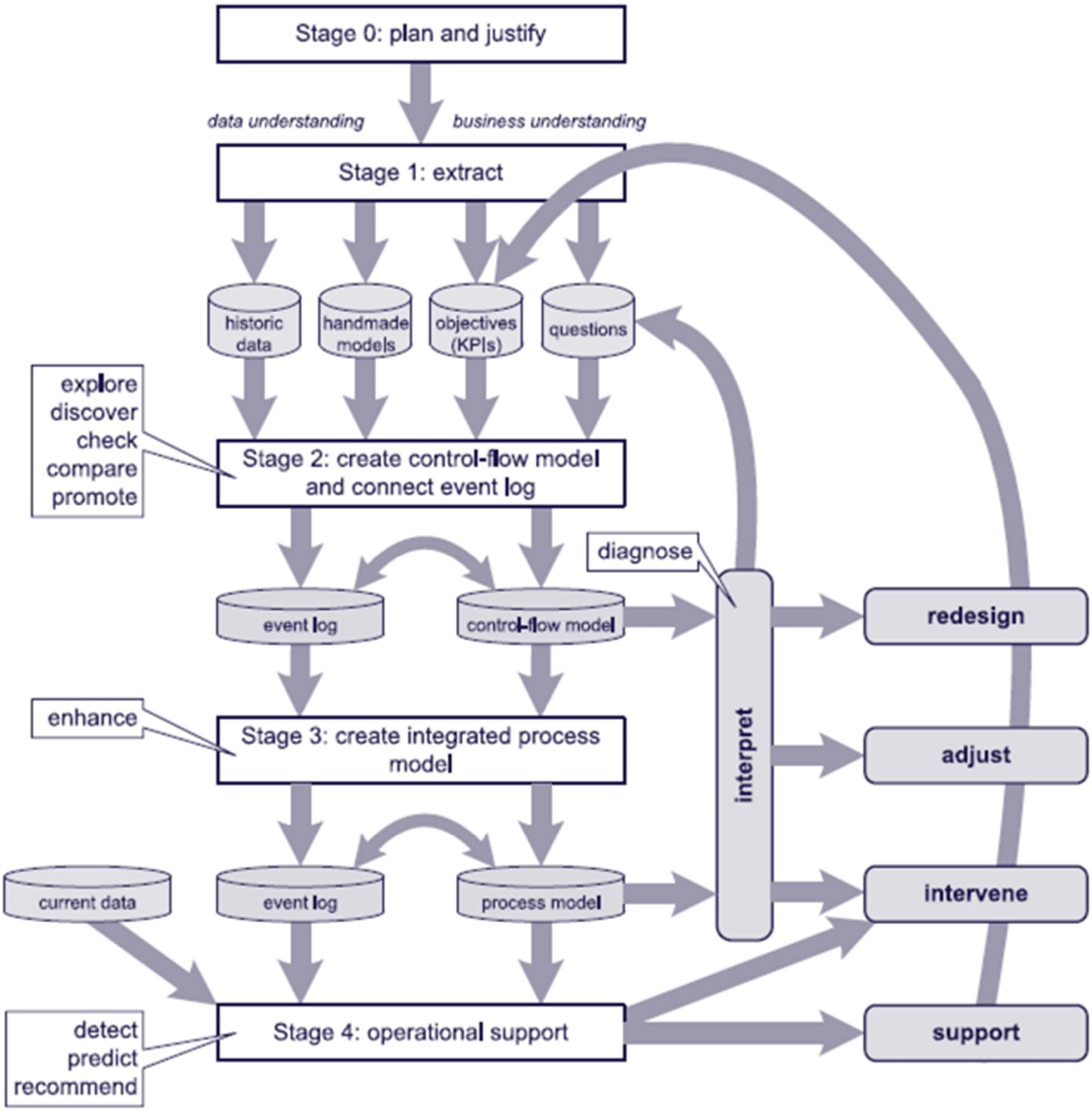

Figure 9. Life-cycle Model of a Process Mining Project (van der Aalst, 2016, p. 394).

Van der Aalst (2016, p. 394–395) states that there are three types of process mining projects: data-driven, question-driven, and goal-driven. For organisations without much process mining experience, it is recommended to start with a question-driven project. Further, a process mining project needs to be planned carefully, with activities scheduled, resources allocated, milestones defined, and progress monitored continuously.

According to QPR (n.d.-b), and as outlined in Figure 10, the process mining lifecycle starts with identifying the process model requirements. This is done by preparation in terms of interviews, workshops, hypotheses, process modelling and ETL data via a connection. Once the preparation is complete, the process model is built, and the analysis can be carried out. This is done via discovering, analysing, turning the model into relevant and actionable data, defining, and developing key success factors and KPIs i.e., creating a new process model. The next step is then to share results of the discovery and analysis. After the insights, actions can be taken in terms of business initiatives and projects, a re-design model and change management, intelligent automation, and system developments. Once complete, business value is generated. The lifecycle is presented below.

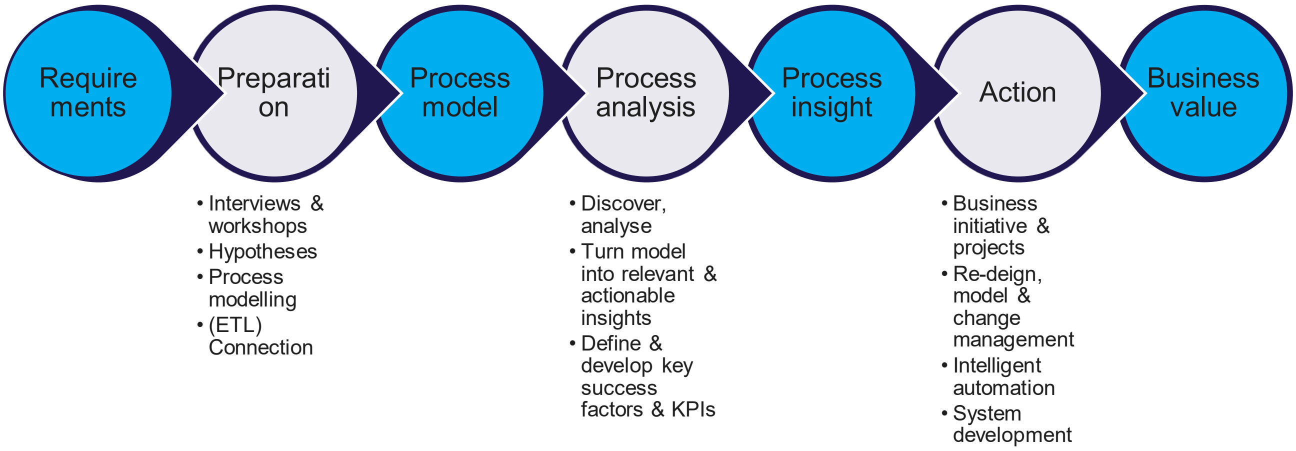

Figure 10. Process Mining Lifecycle (QPR, n.d.-b).

Further, Weske (2007, p. 15) states that as logs are generated from traditional information systems, which can provide a starting point for developing business process models, the evaluation of current process models is also made possible. According to Workfellow (n.d.), once the data is collected, transferred, and structured the comparison of the current and ideal processes can be carried out, this is called conformance checking which includes multiple data analytics, mining, and data science methods. Bottlenecks are located and improvements are suggested based on deviations. However, it is important to note that process discovery records the process in its as-is state with the random deviations and flaws included. Via computer vision, which covers machine learning and Artificial Intelligence (AI) tools, a metamodel of the process, as it was executed by humans, can be created. Thus, root causes and bottlenecks can be identified easier.

2.1.5 Process Mining Challenges

According to reviews on G2 (n.d.), the training to prepare for process mining endeavours can be time consuming, there can also be issues with lack of support from some service providers. Further, Detwiler (2023) indicates that issues faced in the process mining profession include lack of awareness, lack of quality data being accessible, challenges in converting data, the growth of internal process complexity, security, and conformity risks, along with adoption resistance within organisations.

Van der Aalst (2016, p. 182, 449–450) states that although process mining is applicable, it poses challenges which demonstrates it is a young field of study. The real core challenges are said to be in data acquisition, preparation, and interpretation. Process discovery is probably the most vital and visibly challenging part of process mining, sufficiently portraying behavioural aspects of data is the key as this is what the process model is derived from. Hence, if event logs are incomplete and its data is noisy then this has a direct impact on its quality. Nevertheless, these are often not free of noise, nor entirely complete. The key is to attempt to get the ratio as close to 80/20 models as possible, this means simple models which can explain the most likely and common behaviours in the data. Further, spaghetti processes are particularly prone to challenge due to their variability. Van der Aalst concludes that most of the available process mining applications would benefit from a data scientist mindset, rather than broad and complex infrastructures capable of processing and solving problems in a mass scale. Lastly, Weske (2007, p. 32–57) claims there can also be challenges in technical integrations, such as application systems and functionalities, as the data is often stored in multiple locations and defined as various names. For example, CustomerAddress in one system may be referred to as CustAdd in another.

Dumas, et al. (2013) summarise the challenges of automatic process discovery by stating they use event logs to reconstruct process models accurately, but some log information can be misleading due to system crashes. The resulting models may also be complex and difficult to understand, requiring filtering or clustering of the logs for better comprehension. These failure types relating to a flawed storage of event logs are summarised with the term noise.

It is however difficult to find challenges with the QPR platform as there are plenty of promotional material, blogs, and videos which are focused on positive stories and driving sales. Moreso when considering potential failed cases that clients may have had when adopting QPR’s process mining platform, this is most likely due to such information not being public. However, in terms of considering expectations and deliverables, there may be possible challenges posed. For example, Buhrmann (2020, 129–133) states that setbacks can be related to fast and high expectations, and Reinkemeyer (2020) elaborates that exaggerated promises from suppliers and unrealistic expectations from companies and platform users are also pitfall-prone areas. Hence, it would be wise to keep these in mind.

2.1.6 Process Mining Benefits

Roth (2022) compares the traditional process development methods to the benefits of process mining. Upon reviewing Table 1, it becomes apparent that traditional methods are inferior. The reasons for this are due to process mining being able to switch between high level overviews and finer details. Objective data can be analysed by process experts, attention can be paid to important variations in the process, regardless of its occurrence. The most relevant development targets can be found, and the possibility to simulate process changes in advance, thus, automatically updating models and the analysis. This allows for identifying opportunities for automation whilst evaluating the benefits. Also, allowing processes to be analysed deeper, considering both the high-level overview and the finer details. Utilising core data inserted into system(s) across the holistic process, alongside experts, enrichens the opportunities and leads to greater benefits too. Being less receptive to human error and perception in terms of insight, variations in the process, and preconceived issues or missed opportunities in the process. In contrast, a great limitation in traditional development methods, in terms of adopting new process models and analyses, in addition to the workload required in monitoring, questioning, and manually calculating opportunities for automation. Process mining seamlessly identifies these areas, whilst evaluating solutions along the way.

Lehto (2022, p. 19) mentions that traditional, subjective, methods of documenting processes have been conducted via interviews, discussions and human interpretations. Whereas process mining is based on facts and accurate data which can detect changes in operations due to the interactive and visual analytical flows that are rendered in process mining platforms (op. cit., pp. 28–29).

Table 1. Traditional Process Development Methods versus the Benefits of Process Mining (Roth, 2022).

Traditional process development methods	The benefits of process mining
Preselected high level key metrics	The ability to slide between high level and fine details, and gain transparency to the process and metrics at all levels
Based on documentation, personal experience and insight	Based on objective data that is analysed with the support of algorithms combined with process experts
Attention to known and most common process variations	Attention to the most important variations in terms of goals, regardless of their frequency
Attention to already identified issues and development opportunities	Identifies the most relevant development targets in terms of goals
Limited opportunities to assess the overall effects of changes in advance	The possibility to simulate process changes in advance
A large amount of work in updating models and analyses	Automated updates
Identifies automation opportunities by monitoring tasks, interviews and manual calculations	Identifies automation opportunities and evaluates their benefits

According to Uusitalo (2020), the purchase-to-pay process contains an extremely high volume of transactional and often quite complex steps; including approvals, procedures, and suppliers, which can pose potential errors. Process mining can bring visibility to the end-to-end process and identifies root causes for issues such as locating bottlenecks, and non-compliancy. Maverick buying, which refers to unauthorised purchases, is also noted as a possible area to improve. Moreso, as this type of purchasing can lead to greater costs, decreased control, poor contractual terms, and business relationships with suppliers can suffer. Therefore, this type of buying does not only go against the R2P process but can also prove to be detrimental to the organisation.

As a case example, researched by Ser (2021, p 41–49), ABB uses the Celonis process mining tool, the highlighted issues were due to various platforms' data, improving real-time analysis, harmonising master data, and low dependency on various domain architecture. However, the company was able to identify and analyse the root cause of operational waste in their P2P processes, thus improving the process by reducing waste and increasing efficiencies. ABB asserted "it is easier to drive change when the need for change is proven with data and facts" (op. cit.).

QPR's (n.d.-c) procurement solutions highlight four key benefit areas, including reducing maverick buying and finding the root causes of these. Increasing clients' three-way-match rates and automated invoice approvals. Gaining end-to-end visibility of the procurement process and insight into how the process contributes to business outcomes. Predicting and preventing process failures as well as monitoring respective KPIs. There are also pre-made dashboards in QPR to gain process insights, automate notifications when there have been issues e.g., with maverick buying, or when there are predictive late payments identified. Furthermore, the UK Government Digital Marketplace (n.d.) states QPR benefits are transparency in transactions, insights into process abnormalities, highlighting process delays, bottlenecks, issues, locating best practices, comparing current process maps and as-it processes, predictions on outcomes, the opportunity to benchmark and compare, generating dashboards which can outline process overviews, and provide automated clustering analysis for larger datasets.

The overall benefits of QPR's ProcessAnalyzer are outlined in Figure 11, note these have been sourced from the company's marketing materials. QPR can benefit companies by identifying process improvement inefficiencies, compliance issues, locating root causes, considering development resources, and communicating findings via an interactive interface. QPR can process KPI reports, to improve quality, identify root causes, continuously enhance performance by focusing on relevant KPIs, and generate notifications to inform of potential delays in a process. The platform can also support IT and ERP development by focusing on reducing project risks, shortening development durations, lowering costs, and ensuring smooth system migrations. Through digital transformation, QPR can also help understand process contributions to business outcomes, allow for informed and fast decisions, increase operational transparency by monitoring relevant KPIs, and accessing critical information during complex transformations. QPR can also identify suitable and profitable parts of a processes for automation, it can support in monitoring automation rates and ROI, streamlining processes for RPA readiness, and help track various RPA-related metrics. Finally, QPR is auditing and compliance ready, ensuring users full coverage of processes and transactions, thus mitigating business risks, reducing compliance costs through faster analyses, and using predefined analyses and filters for easy reporting.

Process Improvement
- Discover as-is processes, their inefficiencies, and compliance issues
- Find root causes for problems and efficiently allocate development resources accordingly
- Communicate findings to stakeholders through the interactive User Interface (UI)

Process KPI Reporting
- Improve the quality of process KPIs
- Find root causes of problems and poor performance
- Continuously improve process performance by focusing on relevant KPIs
- Get notified when a process step is going to take too long, affecting KPIs

IT & ERP Development
- Reduce risks in all IT and ERP -related projects
- Shorten durations of development projects
- Reduce maintenance, development and implementation costs
- Ensure smooth system migrations

Digital Transformation
- See how processes contribute to business outcomes
- Get current evidence to continuously make quick and thoughtful decisions
- Increase the transparency of operations and monitor the right KPIs
- Get access to the right information during most complex transformations

Robotic Process Automation
- Find out which processes are the most suitable and profitable for automation
- View automation rates and instantly see the ROI of RPA
- Use process insight to streamline end-to-end processes, so they’re RPA ready
- Monitor a variety of RPA–related metrics in ready-made RPA presents

Auditing & Compliance
- Get 100% coverage into all processes and transactions
- Mitigate business risk by identifying and improving risks and violations
- Reduce compliance costs with faster and more accurate analyses
- Use predefined analyses and filters to ensure easy measuring and reporting

Figure 11. ProcessAnalyzer Benefits for Process Mining Use Cases (QPR, 2020).

Finally, the implementation of process mining, according to Ser (2021), emphasises seven key areas: vision and goals, data management, roles and responsibilities, technology, governance, performance management, and change management, in addition, a comprehensive operating model is also emphasised. Successful implementation is said to require management commitment, an iterative approach, openness to change, experimentation, and quick adjustments.

2.1.7 Available Process Mining Platforms

G2 (n.d.) determine there are currently 92 process mining platforms available. Those of which focus predominantly on process mining include IBM Process Mining, Celonis, UiPath Process Mining, Kofax Insight, InVerbis Analytics, QPR ProcessAnalyzer, and Apromore. Roth (2022) states Celonis has led the market for a long time, whilst QPR is one of the oldest and most known suppliers in its field. The process mining providers most often used in Finland are Celonis, QPR and UiPath (op. cit.). Process mining suppliers have reported growth rates of more than 100% in recent years, analysts expect further growth by ten times this rate in coming years (Badakshan et al., 2022, p. 3).

According to G2 (n.d.), QPR ProcessAnalyzer ranked highest of the four when comparing process mining features, especially regarding integrations. The IT and Services industry tend to be the forerunners in utilising process mining platforms although Oil & Energy, Telecommunications, Accounting, Computer Software, Pharmaceuticals, Financial Services, and Mechanical or Industrial Engineering also seem to be adopting process mining platforms too. Celonis appears to be focusing on enterprises (+1,000 employees) as 67.7% of clients reviewed their platform from enterprises. Whereas IBM seem to be in the small-business (50 or fewer employees) as 39.8% and mid-markets (51–1,000 employees) 40.3% of clients reviewed their platform from these forms of organisations. QPR appear to be in both the small-business 41.7% and enterprise 50.0%, however, not so many clients appear to be from the mid-market 8.3%. UiPath seem to have a more balanced range, most customers are from enterprises 48.2% but mid-market 27.9% and small-businesses 23.9% are clients.

For products to qualify for the G2 (n.d.) process mining category, they must include the possibility to track event logs and discover business processes. Based on these, also perform checks to verify variations and conflicts in the process, provide insights where employees possibly deviate from the norm, and integrate with preexisting IT infrastructure the organisation has in place. The added benefit of process mining platforms is that most tools can promote the adaption of RPA solutions which in turn could save the client additional resources and ensure further efficiency.

2.2 QPR Software Process Mining Provider

QPR Software Plc (n.d.-a) is a Finnish company founded in 1991 which offers process mining services. As a current and local supplier, it was the preferred solution for Wärtsilä’s Indirect Procurement department since there is an existing agreement in place. Thus, scope and platform(s) could be extended without project delay nor unforeseen costs. After the initial meeting with an internal analyst, who is an expert on process mining, it became apparent that QPR were originally selected as the company’s provider due to the maturity of the existing platform and data security reasons. Further, the Snowflake (n.d.) platform which allows siloed data to be unified at greater magnitude with superior loading times, increased the memory and data storage immensely. Thus, resulting in a more powerful analysis by allowing background data to be more realistic and live in-time and allowing for more value to be generated from the data.

QPR (n.d.-d) claim that process mining can be utilised in the procurement process, made possible via their QPR ProcessAnalyzer tool. Clients extract data from their information system(s) and use the tool to visualise a real-life execution of the company's process flows. This is then combined with other insights drawn from event logs.

According to G2 (n.d.) QPR ProcessAnalyzer has less market presence than its main competitors. However, the satisfaction rates are strong in terms of ease of use, execution management, process library and application development, QPR scored above average on all four fronts. QPR scored top 6th process mining software in Europe. The platform has connectors available for all major operational systems such as SAP, Oracle and ServiceNow. It is also recognised by top industry analysts. It has a leading root cause analysis thus allowing companies to easily notice operational inefficiencies, bottlenecks, and compliance issues.

2.2.1 The QPR Process Mining tool

According to QPR, their ProcessAnalyzer would manage the process mining lifecycle from end-to-end i.e., from the requirements through to the business value stages (ref.

Figure 10. Process Mining Lifecycle (QPR, n.d.-b).). Further, the company's slogan and promise is "Discover. Optimise. Automate". However, there are key roles required in the client organisation to ensure the project runs smoothly, these include; Developer(s) who will carry out the preparation and create the process model, plus supporting in the process analysis step, and Analyst(s) who will carry out the analysis and derive the insights from the model, further supporting the client's Business Users in pushing for actions to create business value by optimising the process.

QPR (n.d.-b) state they currently provide solutions for SAP transformation, intelligent automation, process intelligence, auditing, procurement, order management, digital transformation, IT & ERP development, service management, and logistics. Apparently, all industries can utilise process mining, the same applies for applicable processes, however, as with process mining in general the requirements are that an IT system is in place with CaseIDs, which logs events, the type of event and timestamps.

Moreso, QPR (n.d.-b) elaborate that metrics the process mining tool can calculate include customer satisfaction and internal efficiency, once these are on a good level it is possible to begin with process automation, where individual steps in the process can be automated. However, QPR claim it is also important to streamline and improve customer satisfaction, as well as internal efficiency prior to automating processes. This is to avoid poor performance from being provided at a faster rate. Thus, a combination of these three components generates process excellence, which in turn allows for increased profits.

Lastly, the QPR (n.d.-b) process mining maturity model claims to include the past, present, and future data. The past data is said to identify the process exceptions and seeks out root causes to reduce process waste. The present data is utilised for on-going data such as process KPIs and monitoring performance. The future data should identify problems using predictive analytics and prevents problems for on-going cases. These combined are the latest capabilities of process mining, according to the service provider.

Lehto (2020, p. 99–108) provides customer case examples where QPR ProcessAnalyzer has been used by Metsä, EY, and KBC. Metsä were able to identify key areas for process improvement, enhancing customer satisfaction through better delivery accuracy and efficiency. The tool was said to provide valuable insights, allowing targeted improvements without trial and error. Continuous monitoring ensures development activities are based on data, leading to better customer service. EY were able to understand root causes and take corrective actions to improve operations. The tool's machine learning and AI features, such as clustering analysis and case level prediction, quickly help to analyse transaction-based data. Key features appreciated by EY include root cause analysis, conformance analysis, and business process modelling. KBC were able to identify root causes of inefficiencies and track service level agreement (SLA) performance i.e. the service expected from a customer. The tool helped uncover issues like a bottleneck in the e-form system, which doubled processing times. By analysing bottlenecks and root causes, KBC reduced throughput times. Key features appreciated include influence analysis, clustering, and predictive models.

2.2.2 QPR ProcessAnalyzer Capabilities

Process discovery will be carried out in the QPR ProcessAnalyzer tool, however, in preparation for the empirical study, trainings on the platform have been deemed necessary. Thus, during these trainings, notes have been made to ensure that the empirical part goes smoothly. As an introduction into the upcoming methods and process, examples and theoretical backgrounds within the tool are provided in this section.

QPR (n.d.-b) claims their process flowchart contains process paths which include the flows within the process, an example of this can be found in Figure 12. Each case contains a CaseID, which logs events, the type of event and timestamps. In the example below, the CaseID would be a Purchase Order (PO) number, where the event types would include Shopping Cart Created, Shopping Cart Approved, PO Item Created, Goods Receipt, Invoice document, Goods Receipt, Invoice Receipt, Invoice Payment, Invoice Due date. This means that one case has twelve events including eight distinct types, as there were multiple goods receipts performed against this purchase order. The process model used in QPR ProcessAnalyzer is PetriNet. There is also a built-in tab called Enhanced BPMN, it is embedded as bpmn.io which is an open-source web-based solution and is powered by Camunda Services (n.d.).

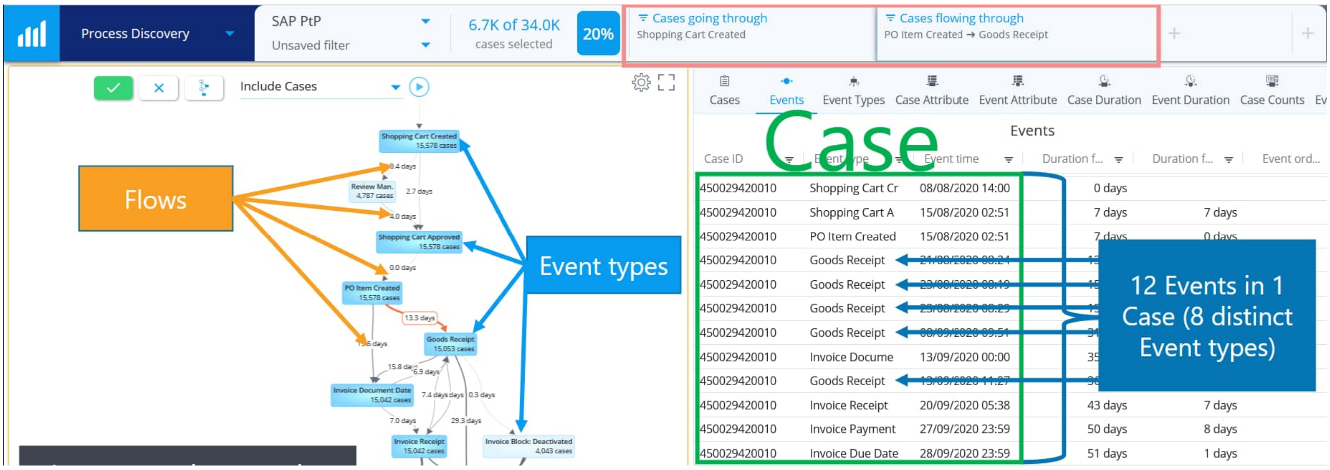

Figure 12. An Example of Process Discovery in the Purchase-to-Pay process (QPR n.d.-b).

According to QPR (n.d.-b), the Root-Cause analysis part of the tool can be described as an AI-based method. It is used to identify correlations between process behaviour, connected process activities and case attribute values. It is possible to analyse case durations, occurrences of process activities, non-conformances, and root cases for poor KPI performance. The tool divides the cases into two parts; where process behaviour or KPI outcomes occur and where they do not. Visually the flowchart then pinpoints these by highlighting above and below average tendencies. It is then possible to dig into the events in depth via the process flowchart and compare the cases with case attribute values. Those which are impeding are the positive impacts on the process and the contributing cases are negatively impacting the process.

In addition to Root-cause analysis, there are ten other analysis opportunities in QPR. These include Case analysis, Events analysis, Event type analysis, Case duration analysis, Event duration analysis, Case counts analysis, Event counts analysis, Variations analysis, Flows analysis, and Clustering analysis. There are also profiling opportunities, these include Case attribute profiling, and Event attribute profiling (QPR Software, 2019).

With regards to the analysis types QPR Software (2019) expresses that Case analysis includes insight into details such as case ID, case start and end times, case duration, latest event, events count and count of event types. Event analysis provides data on individual events, including case ID, event type, event time, duration from case start, duration from previous event, and event order in each case. Event type analysis aggregates data for each event type, including the number of cases containing the event type, total events occurred, events per case, incoming flows, and outgoing flows. Case duration analysis breaks down case counts by end-to-end duration, with customisable granularity and visualisation options. Event duration analysis examines flow duration between selected events, which is useful for subprocess analysis. Both analyses provide customisable time units and visualisation settings, including cumulative distribution displays. Case counts analysis breaks down case counts based on event timestamps over time, with options to change the event type, time granularity, and visualisation type. Event counts analysis similarly breaks down event occurrences over time with adjustable time granularity. Variation analysis is a tool for identifying common process variations, deviations, and sources of rework. It ranks different combinations of process steps by their frequency in cases. Key metrics include the specific sequence of steps, count of cases with the variation, average duration, count of events, and count of event types in the variation. Flows analysis aggregates all start to end event flows and sorts them by average duration. It analyses incoming and outgoing flows per event type, including start and end event names, average and median durations, case counts, flow occurrences, looping percentage per case, and standard deviation of flow duration. Clustering analysis is an AI tool for grouping similar cases by selecting clusters, cluster items, case attributes, and event types. Columns include Feature (common case attributes and event types), Cluster Density Percentage (share of cases with the feature in the cluster), Total Density Percentage (share of cases with the feature in the dataset), and Contribution Percentage (cases explained by the feature in the cluster).

Further, with regards to profiling, Case Attribute profiling visualizes case counts by attribute values, with options to select different attributes and change the default bar chart visualization. Event Attribute profiling does the same for event counts. Lastly, QPR's training includes how to visualise the data using different charts and how to interpret the results to identify patterns, rework, looping, and process variations. Additionally, it outlines AI-assisted clustering to group similar cases and the importance of root-cause analysis in understanding process behaviours and improving business operations (QPR Software, 2019).

2.2.3 The Evolution of Process Mining & Snowflake

Bergman (2023) states process mining initially emerged in manufacturing and production processes. However, it has since been applied to other processes. Integration with RPA and BPM allows for innovative optimisation of business processes. Machine learning and artificial intelligence are being used to improve the accuracy and effectiveness of process mining. These technologies allow organisations to analyse and interpret large amounts of data, and to identify patterns and anomalies that would be difficult or otherwise impossible to detect. Deep learning techniques will allow process mining platforms to detect patterns and render more accurate and useful predictions. By enabling continuous data analysis, organisations can swiftly identify and resolve real-time challenges, thus enhancing their agility and responsiveness. Process mining is expected to continue evolving, thus, playing an increasingly important role in streamlining operations and efficiency.

Bergman (2023) elaborates that process mining enthusiasts have been waiting for a scalable solution, which the largest companies can use without compromising their data volume or facing significant performance issues. Many suppliers undertake poor scalability by splitting data into smaller pieces, but this results in losing valuable insights into end-to-end processes (op. cit.). Process mining powered by Snowflake is said to provide real-time process mining at an unlimited scale, ultimate governance, and security, and enables secure collaboration across units and applications (op. cit.). Further, process mining suppliers are said to be under pressure to develop software that is more accessible to a wider range of users (op. cit.). The use of process mining will develop even further from analysing independent processes to a holistic, enterprise-wide process optimisation, where organisational and social mining come into play (op. cit.). An increase in process mining tools will become available that are cloud-based, and easier to integrate with the other IT systems used by organisations (op. cit.). The future of process mining looks very promising, according to Bergman, with many exciting developments and opportunities ahead (op. cit.).

Do (2022) states that in 2022 QPR Software has collaborated with Snowflake to release a version of its process mining software, QPR ProcessAnalyzer, that runs natively on the Snowflake data platform to ensure clients' future requirements can be met, thus staying ahead. The latest version is said to provide organisations with scalability and performance in the fast-growing process mining market. As well as enabling the utilisation of varied, yet factual data, and decision-making based on it. Snowflake's modern technology can scale to substantial amounts of data, thus, potentially allowing process mining to be applied where it previously had to be broken down for manageability. In conclusion, Snowflake (n.d.) is a platform where its clients are said to be able to store and access structured, semi-structured and unstructured data in one location and gain access to external data with scalability and speed, whilst ensuring governance and security by end-to-end encryption. Thus, its appeal to suit QPR is evident.

2.3 Key Things to Remember

Van der Aalst (2016, p. 451) states process mining tools can handle event logs with billions of events, this implies an enormous responsibility. Thus, impartiality, confidentiality, transparency, and precision should be held in high regard to those conducting process mining. It is also important to avoid unfair conclusions, answer questions without revealing secrets, ensure accuracy, and clarify results. This communicates that process mining should be done in a responsible manner. In addition, it is important to underline that management should not misuse process mining, as people who deviate or delay the process may have good reasons for doing so. Instead, management should focus on positive deviants and not blame individuals for handling difficult cases.

Another suggestion is to avoid unintended leakage of information, for example, by using randomisation or hashing, the reason for this is that most questions can be answered without revealing sensitive information (van der Aalst 2016, p. 451). Further, the burden of attributes and overfitting may lead to false results. Hence, the analyst should assess and communicate the confidence level of the information, conformance checking, and cross-validations. Process mining should be able to provide explainable and traceable results, be understandable by humans, and analyses should be reproducible.

Van der Aalst (2016, p. 118, 449) further clarifies that representational bias should be considered in newfound process mining approaches, as many approaches have used graph-based notations which does not make sense since there are deadlocks and disconnected parts of the data displayed. Workflow nets, BPMN models, and Event-driven Process Chains (EPCs) are recommended as they can represent processes which are not sound. That is, a deadlock or activity that can indeed not be activated.

2.4 Theoretical Conclusion

QPR seems to be a viable choice for reasons including the real-time vast data management with high governance and security, which represented by BPMN models allows for optimised processes and automation efforts to be identified, whilst analysing cases of non-conformities and locating root-causes directly linked to process performance.

The identified challenges according to the theory include data acquisition, preparation, and interpretation. Process discovery is said to be the most vital and visibly challenging part of process mining. Whilst the benefits are said to include transparency to the process and metrics, objective data analysed by algorithms and process experts, attention to the important variations in terms of goals, identifying the relevant development targets, simulate process changes, automated updates, identifying automation opportunities and evaluating the benefits of these. Further, more specifically in relation to procurement solutions highlighted by QPR, **the four key areas are reducing maverick buying, increasing three-way-match rates, gaining procurement process end-to-end visibility, and predicting and preventing process failures**. This therefore concludes that whilst there are benefits to be valued from in process mining, it is apt that challenges are paid attention to and respected in the project – this is the first step and priority.

As discovery, conformance, and enhancement are the three main forms of process mining these will be focused on in the empirical section. Discoveries can be made based solely on the event logs, so this should be the second goal. Conformance compares event logs with an existing process model to uncover, clarify, and measure deviations, so this should be the third goal. Enhancements are used to improve a process model via the event log, this is where bottlenecks and performance can be identified, so should be the fourth goal. Thus, the above concludes the theoretical study on how the QPR tool can be utilised in the R2P process by Indirect Procurement, as well as what techniques are required to ensure process mining is successful.

3 EMPIRICAL STUDY

Chapter 3 (37 pages) are omitted as they contain sensitive business information.

4 CONCLUSION

The typical process which purchasing departments follow begins with the trigger of a need to procure goods/services, also known as a request. The next steps involve sourcing and generating a PO, receiving a confirmation from the supplier, receiving the goods/services, the invoice related and some method of approval for the invoice to be paid. Deviations to the process can cause issues both in the internal process, but also in the external process (supplier's side) since quotations, sales orders and supply invoices as well as queries or disputes related to invoices from customers can cause additional manual work and potential retractions, re-work, additional emails or other communications and in the case of invoices, credit note and new invoice allocation requirements too.

QPR ProcessAnalyzer can provide valuable insights into business processes, locating bottlenecks, inefficiencies and areas of improvement. By analysing complex datasets companies can make more informed decisions based on real-time process performance rather than assumptions or intuition. This can lead to streamlined processes, an increase in productivity and cost savings in the long-term. The platform can also support in ensuring compliance by capturing deviations from expectations and reducing risk of errors. Automation detection is also possible as the platform discovers repetitive tasks and manual interventions, thus, allowing resources to be freed up for more value adding initiatives. However, managing complex data can be challenging, it requires specialised skills to provide meaningful and actionable outcomes. Certain types of data may also be difficult for the platform to manage or may present such data in a complex manner due to complex process scenarios. Additional resources and expertise can therefore be required, which can lead to more time and financial impediments.

As outlined in the thesis theoretical part of this study, regarding the lifecycle model of a process mining project (Figure 9), the process between transforming the event log data, control-flow model and process model was the most time consuming and difficult part of this project, it was not expected to take almost a year. Current system data was used to support in the detection, prediction and recommendation part where operational support was utilised as a validation mechanism. Such interventions, adjustments and redesigns were possible during the transcript phase although this is where the project's main delays arose.

> "The most important outcome from a process mining perspective was the discovery of the main flow... process mining from an organizational perspective focused

> on… the identification of places in the process where the circling of work is undesirable.” (van der Aalst et al., 2007, p. 25–26)

As van der Aalst et al. state in the above quote, the vital process mining outcome is finding the flow, however, from an organisational viewpoint the process flow’s details and analysis on the data is the valuable part of process mining. Therefore, the operational validation played a vital role in this procedure.

The project did not only face challenges related to data transformation, but time allocation and the need for additional expertise and support from QPR was necessary to ensure further delays were avoided. While most objectives were met, the process required more collaboration, clearer goals, and additional resources. The project has shown vast potential and has already started to pay off, but there were areas for improvement to achieve more comprehensive and faster results. The tool was not primarily aimed on freeing up time, it provided valuable data regarding business cases and process improvements which confirmed the development priorities and displayed a positive return on investment to management. The tool's benefits in compliance and process monitoring also contributed to its overall value. The main limitations included unfamiliarity with the tool, data extraction and transformation challenges, lack of dedicated resources and expertise, and difficulties with specific types of data. These limitations affected the project's ability to achieve its maximum potential. The interviewees’ recommendations stressed the importance of proper planning, collaboration, data quality, and adequate support to ensure the success of process mining projects.

To answer the first research question, the QPR ProcessAnalyzer platform can be utilised in the R2P process by identifying bottlenecks in the process. Such as in the invoicing part, which highlight areas where improvements can be made. Moreso, process analysis and improvement to allow teams to focus on positive changes and the impact of these in the process. As well as real-time analysis capabilities, which can serve as a foundation to discuss ways of working and possible changes required. Training and knowledge sharing should be done to promote the use of the platform, as well as creating dashboards which allow accurate data to be presented to management in a professional and appealing manner. Continuous feedback to QPR can also help them improve the platform, their level of support and communications regarding product releases. Finally, leveraging the platform’s capabilities for increasing efficiency and effectiveness, allowing the IP team to serve its internal customers better.

To answer the second research question, the techniques in ensuring process mining endeavours are successful, include dedicated resources which can yield faster and more extensive results. Having a project team with technical backgrounds to enhance the effectiveness of process mining, whilst ensuring data accessibility, as this is fundamental to succeeding. Furthermore, combining self-made models with QPR expertise, to ensure correctness and reduce project delays. Although dashboard have been mentioned in how the tool can be utilised, they are also important for ensuring the success of a process mining project as they reflect the benefits and present ROI to management. External partners, such as QPR, should be regularly involved in keeping the project on track, to ensure it succeeds. Further, establishing clear objectives and data requirements at the beginning of the project is essential, although having an iterative approach is often necessary as new data needs are discovered. Tool providers should be proactive in sharing knowledge, supporting their clients, and networking to ensure long-term success, this also involves time management and potentially leading process mining projects to build rapport. Promoting the tool and providing training can support with wider adoption and effective use, thus supporting a continuous improvement mindset and success overall of such a project. Finally, feedback to the tool providers can ensure that developments occur, which also supports process mining techniques being further developed, bringing added value to the clients.

Each step of the process can be analysed, either as a whole or as a portion for further granularity. Rework analyses were the starting point of the analysis, at each portion of the process for deeper diving into the data. Then key performance indicators and process performance indicators were considered, as they are the department’s current goals, and deviations related were scrutinised. Process developments were made along the way, and management saw the figures based on QPR Dashboards, allowing them to make decisions based on real-time data and utilise it to their advantage. Additional recommendations have been noted to guide internal stakeholders when placing purchase requisitions, and robotic process automations have been also highlighted to remove mundane tasks from operations.

4.1 Limitations

Limitations of this research were due to time constraints and workload in other developments, projects and daily tasks, it was not ideal that the internal project team were not able to progress as swifty as initially anticipated. Alas, the biggest constraint was the lack of awareness regarding the vast resources required in data transformation, as well as how complex this would be. The project team had only one person able to perform this task and although an internal colleague who had been transforming data in QPR already was able to support, it was mandatory to consult with QPR and ensure that prior attempts had been exhausted to manage this alone, this is where the ultimate limitation truly lay. In addition, one of the project team members had a long-term absence and this also impacted the progress. Nevertheless, the project was picked up again once the limitations were overcome.

Process mining, according to Workfellow (n.d.), is limited to the steps timestamped in the system(s) that are fed into the tool. Thus, this ignores the human factor of a process, whether it be meetings or guidance provided over email or a chat client, the documentation involved in the process, or applications which are related to productivity. Furthermore, if a lengthy process is being analysed then misleading results may occur due to the process step not being technically deemed significant to the flow (op. cit.). Hence, it is good to be aware of this and scrutinise the data that is being analysed by testing and examining outcomes.

Other risks which were considered, include legal risks, such as a non-disclosure agreement (NDA) to protect the confidentiality of both companies' commercial and sensitive information. As well as technical risks in terms of IT security, since the companies' platforms would be connected. However, these risks were not issues since these aspects were taken care of prior to this study commencing due to an existing cooperation and agreements in place.

4.2 Recommendations

It would be recommended that the initial investment in transforming the data would combine the clients' internal personnel on a temporary full-time basis, or part-time basis with clear outlined working time, in addition to being prepared to actively reach out for support from the platform provider. If this type of project is not prioritised correctly, or management see this as a cost rather than an investment the likelihood of the project success is slim.

To improve the cases analysed in Wärtsilä's Indirect Procurement's R2P process, implementing standardised procedures, providing targeted training, and considering automation for consistency and accuracy is advised. Moreover, conducting root cause analysis and streamlining processes to reduce rework, as well as performing regular audits, maintaining documentation, and encouraging continuous improvement. Similarly, forming cross-functional teams, holding regular meetings, and providing clear guidelines for communication and case issue resolutions. Utilising data analytics, workflow management tools, and ensuring system integration to reduce errors would assist in efficiency too. Besides implementing data validation checks, regularly cleansing data, and establishing a master data management strategy. Further, providing role-based training, encouraging continuous learning, and offer certification programs. Finally, defining KPIs, creating dashboards, and benchmarking performance to identify areas of improvement. By implementing the recommendations based on the key findings from the analysis, it would be possible to reduce rework, enhance the overall efficiency and effectiveness of handling cases in the R2P process.

The Deming Cycle, otherwise known as the Shewhart or PDCA cycle, could be an ideal approach to analysing the issues, identifying the root causes, and planning the improvement, implementing the change at a smaller scale and studying the results, further verifying if there are still issues, then placing the solution into action and monitoring the change in QPR (Swamidass 2000, p. 155). The BPM Lifecycle could also be utilised to provide an overview of the process steps, first by existing process mapping and the design of an improved method, then by envisioning how the process should be, implementing the new process and managing the flow, tracking the performance, finally analysing the outcomes to allow for adjustments continuously (Dumas et al., 2013, p. 16). Additionally, process excellence (PEX) refers to the continuous improvement and optimisation of business processes (Turdibayeva, 2024). It focuses on streamlining processes, ensuring desired outcomes are met, whilst maintaining high quality, enabling agility, and fostering innovation (op. cit.). Methodologies related include Lean, Six Sigma, Kaizen, and BPM are commonly used (op. cit.). Do (2020) states the happy customer, flow and automation are at the centre in QPR, by keeping its promises to clients, on time and accurately, via a first-time right mentality with lead time consideration, as well as promoting automation for touchless flows. Thus, this provider can be recommended.

As a final recommendation, additional case studies could have enriched this study further, especially when comparing the adoption of process mining tools, methodologies, challenges faced and solutions to these. In addition to further emphasising how the platform could be otherwise utilised, and potential alternate techniques that could ensure process mining platforms are adopted competently, efficiently and successfully by organisations.

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APPENDICES

Appendix 1. Training Steps

Basics of QPR ProcessAnalyzer

- Introduction to Process Mining, completed 25.8.2023
- Introduction to QPR ProcessAnalyzer, completed 28.8.2023
- Introduction to Process Discovery, completed 28.8.2023
- Filtering exercises with Process Discovery, completed 4.9.2023
- Introduction to Root Cause Analysis, completed 5.9.2023

Basics of Dashboards and KPIs

- Dashboard 1: Creating a simple dashboard, completed 5.9.2023
- Charts 1: Introduction to Chart Settings, completed 5.9.2023

Certifications

- Value Creation Specialist, completed 5.9.2023
- Process Analysis Specialist, completed 2.2.2024

Appendix 2. QPR Training Glossary

Case analysis shows each individual case within the data in their own rows:

- **Case ID:** The individual identifier assigned to a case.
  - **Case** start: Time stamp of the first event of the case.
  - **Case** end: Time stamp of the last event of the case.
  - **Case duration:** End-to-end duration from the first event of the case to the last event of the case.
- **Latest event:** Last event in the chain of events of the case.
- **Events:** Count of event occurrences in the case.
- **Event types**: Count of event types in the case.

When # Events > # Event types, there is an indication of rework/looping in the individual end-to-end process.

Events analysis shows each individual event within the (filtered) data set in their own rows:

- **Case ID:** The individual identifier assigned to a case.
- **Event type:** Name of the event.
- **Event time:** Time stamp of the event.
- **Duration from case start:** Duration between the event and the first event of the case.
- **Duration from previous event:** Duration between the event and the event preceding it.
- **Event order in case:** Sequence/index number of the event within the case.

Event type analysis shows each individual event type within the (filtered) data set in their own rows with their respective aggregated information:

- **Event type:** Name of the event.
- **Cases:** Count of cases containing the event type.

- **Events occurred:** Event count of the event type in all (filtered) cases.
- **Events per case:** Calculation rule: Events occurred / Cases.
- **Incoming flows:** Number of event types directly preceding the event type within the selected cases.
- **Outgoing flows:** Number of event types directly following the event type within the selected cases.

Case Attribute profiling visualizes the breakdown of the case count according to Case Attribute values. You can select different Case Attributes to analyse by clicking on the drop-down menu. The Visualization defaults to bar chart which you can change from the "Visual" tab of the Chart Settings.

Event Attribute profiling visualizes the breakdown of the event count according to Event Attribute values. You can select different Event Attributes to analyse by clicking on the drop-down menu. The Visualization defaults to bar chart which you can change from the "Visual" tab of the Chart Settings.

Case duration analysis breaks down the case count according to the end-to-end duration of the cases within the (filtered) data set. You can choose the granularity of the distribution of case durations from the "Time unit" drop down menu from weeks to months for instance. The Visualization defaults to column chart which you can change from the "Visual" tab of the Chart Settings. To show the cumulative distribution of durations click on "Cumulative percentage" below the chart.

Event duration analysis breaks down the flow duration between two selected events. This is very useful for analysing the duration of a sub-process, e.g., Purchase Order Registration to Sales Order Creation or Sales Order Creation to Goods Issue. You can choose the analysis target by either: Selecting a flow from the flowchart. Clicking on the "Start" and "End" drop down menus on top of the Event Duration Analysis chart and selecting the desired events. You can choose the granularity of the event durations from the "Time unit" drop down menu. The Visualization defaults to column chart which you can change from the "Visual" tab of the Chart Settings. To show the cumulative distribution of durations click "Cumulative percentage".

Case Counts analysis breaks down the Case Count based on the timestamps of specific event occurrences across time. When a model is first opened the chosen Event defaults to the most common Event type in the data model. You can change the specific Event from the "Event" drop down menu. You can choose the granularity of the time periods from the "Period" drop down menu, e.g., week, month, quarter, year. The Visualization defaults to column chart which you can change from the "Visual" tab of the Chart Settings.

Event Counts analysis breaks down the Event Type occurrences based on the timestamps of specific Events in the data and distributed across time periods. You can choose the granularity of the time periods from the "Period" drop down menu.

Variations analysis is a great tool for identifying the most common process variations (or happy paths) as well as common process deviations and sources of rework. The Variation Analysis identifies different combinations of process steps and their sequential orders and ranks them according to in how many Cases the specific sequences occur. When the number of Events in case exceeds the number of Event types in a Case, we can identify rework and/or looping in the process.

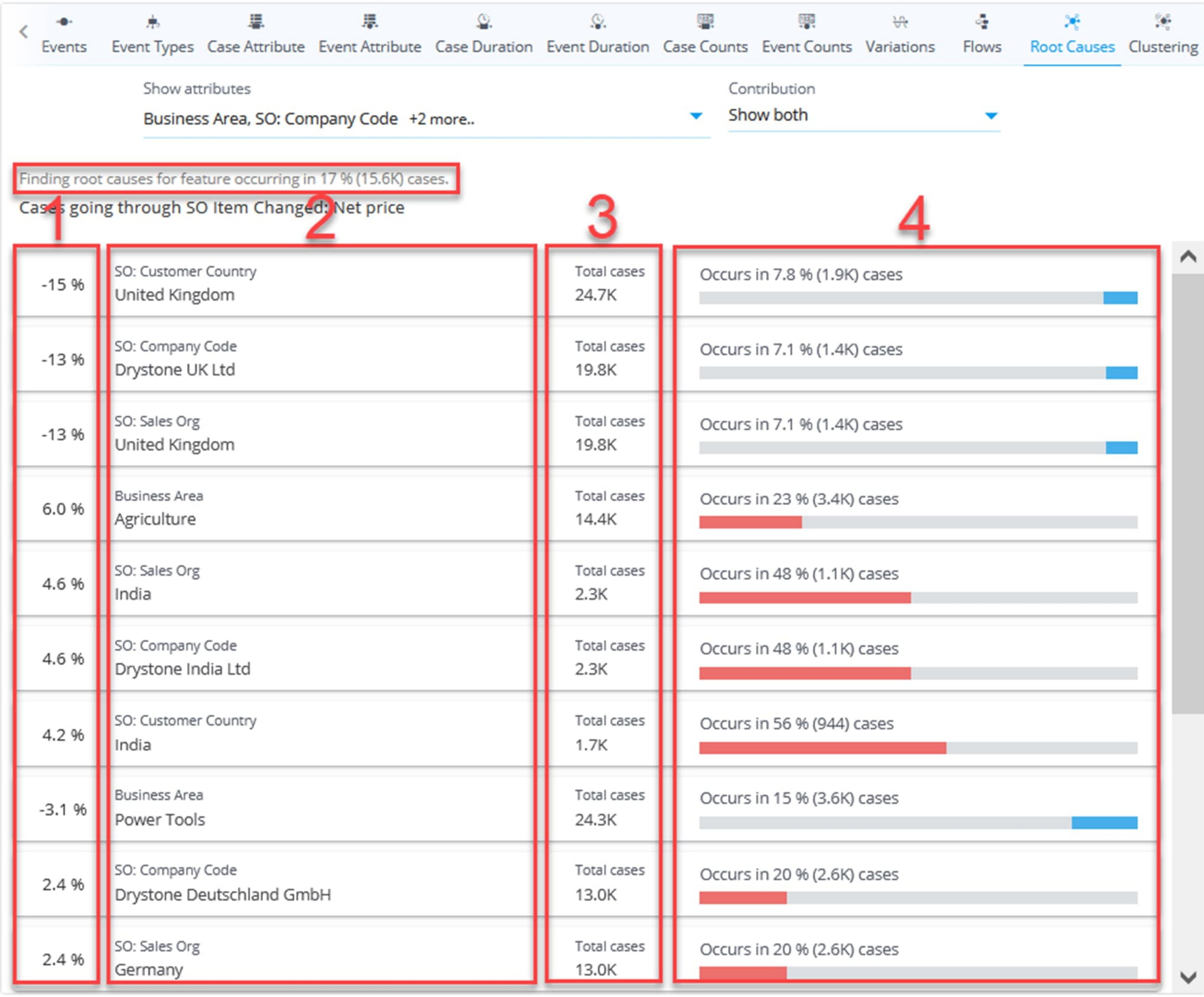
- **Variation:** Specific sequence of process steps (including repetitions)
- **Cases:** Count of cases containing the specific process flow variation
- **Average duration:** Average end-to-end duration of the specific process flow variation
- **Events in case:** Count of occurred events in the process flow variation
- **Event types in case:** Count of event types in the process flow variation

Flows analysis aggregates all start event to end event flows and sorts them in a descending order of Average duration of the flows. It can be used to analyse for instance all incoming and outgoing flows per Event Type:

- **Start:** Name of the start event of the flow.
- **End:** Name of the end event of the flow.
- **Average duration:** Average duration of the flow.

- **Median duration:** Median duration of the flow.
- **Occurred in cases:** Count of cases which contain the flow.
- **Occurrences:** Count of flow occurrences.
- **Looping percentage per cases:** Looping percentage (repetition per case count). Calculation rule: (Occurrences / Cases - 1) * 100.
- **St.dev.:** Standard deviation of the duration of the flow

The idea of ***Root-cause analysis*** is to see whether some Subsets of data (=Case Attributes) correlate with any selected process behaviour. Moreover, to provide insights where to focus business initiatives to maximize or minimize the selected process behaviour.



For example: Order Price Change ratio is on average 17%. Is it 17% through all the case attributes such as Purchasing Country or is the Order Price Change ratio potentially 2% in Country X and 9% in Country Z. -> Best practices from Country X to be rolled into Country Z operations.

- **Header:** Average of the analysed feature in whole data model. Used as a benchmark for all the data subsets e.g., dimensioning with all case attribute values and seeing whether there are any subsets of data which have a higher or lower average.
- **2nd Column:** Subset of data: Case Attribute + Concerned Case Attribute value e.g., Case Attribute: SO: Customer Country: United Kingdom
- **3rd Column:** Case count within the Subset of data (see column #2), 24 700 cases
- **4th Column:** Percentage of the cases having the analysed feature in the concerned subset of data e.g. Case Attribute Value SO: Customer country: United Kingdom has 7.8% of orders having the analysed features (Order Price Changes). Note. Clearly lower than global average 17%.
  - **1st Column:** Because the subset of data (e.g., concerned case attribute value for example SO: Customer country: United Kingdom) has a lower or a higher percentage of cases having the concerned feature compared to global average, it is responsible for X% of the whole featured effect. In other words, how many cases too many/too little there are in this Data subset compared to global average. Finally, this number of cases is divided by the total number of cases having the analysed feature to make it a “contribution percentage”. This means that global average is now 15% lower than it would be if United Kingdom was on a global average level 17% (contracts to 7.8% what it currently has).

Clustering analysis is an AI assisted tool used for identifying and clustering together Cases which are highly similar to each other and can therefore be seen as correlating with each other. You can use it by selecting the number of clusters, number of cluster items (cluster rows), which Case Attributes and Event Types you want to look at. The columns represent the following information:

- **Feature:** This column lists case attribute values and Event Types that are common to the cases in the cluster.
  - **Cluster Density %:** Share of cases having this feature value within the cluster (i.e., the number of cases having the value shown on the row in this particular cluster divided by the number of cases in the cluster * 100).
- **Total Density %:** Share of cases having this feature value in the whole data set (i.e., the total number of cases having the value shown on the row divided by the total number of cases * 100).
  - **Contribution %:** Number of cases that can be explained to belong to this cluster because of this feature value. The scale is such that 0% means that the feature value isn't specific to this cluster and 100% means that all cases belonging to this cluster can be explained by this feature value.

Appendix 3. Qualitative Interview

Interview agenda sent, prior to the interview, in the meeting invitation:

- Process mining; what, why, when, benefits, drawbacks – high level experience
- Objectives
- ROI – calculations / business case
- How did the project go
  - First step: data Extract, Transform & Load (timestamp, log, logic correct)
    - delays loading data
    - examine/transforming requirements and possible data noise
    - errors/issues
    - security
    - testing
    - other
  - Process model
  - How was the tool utilised
  - What techniques were required for ensure the project was successful
- Limitations
- Recommendations

Appendix 4. Interview (EW 10.6.2024 11–12am) Summary

Key points:

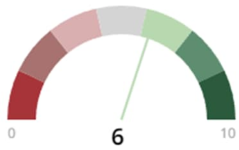
- The project time frame was tight, and support from QPR should have been obtained from the beginning.
- SQL scripting was a challenge, especially without guarantee on the data quality.
- Prior knowledge of PowerBi reports did not translate to expertise in Process Mining, making it difficult to transform raw data efficiently.
- Transforming SQL data tables went well, but not-SQL data objects (like requisition data from Coupa) required importing Excel and CSV files.
- SAP data ETL was already conducted by another business function, which was fortunate.
- Oracle was not useful in the detailed process mining context, and consuming data from SAP through scripts was not ideal.
- Verifying columns and rows in scripts with thousands of rows was difficult, and support from other functions was necessary.
- QPR should have informed that the data transformation was too complex to be done independently.
- Snowflake syntax of SQL was clear and easily scalable with existing skills.
- Building efficient SQL code for process mining was important for data query and loading time.
- Errors and issues came from the data log perspective, and manual work was required for exports and frequencies.
- Time allocation and data issues caused project delays.
- The analyst learned by doing but verifying the correctness of the data was time-consuming.
- QPR support and heavier SQL scripting should have been in place from the start of the project.
- The customer checked the scripting, and data errors needed to be verified.
- Security measures like audits and NDAs were in place, but reassurance from QPR would have been helpful.

- Understanding SQL scripting and process mining concepts was crucial for successful implementation.
- Testing as you go worked well, and updating data transforming scripts into Snowflake caused a delay in the project timeline.
- Collaboration with process experts can enhance the user experience and make the data more usable and actionable.
- Further development areas include workshopping with process experts and creating dashboards for management and process operations.

Thus, highlighting the challenges and considerations involved in using the QPR platform for data transformation and process mining. There is emphasis on the importance of support from QPR, the complexity of SQL scripting, the need for data verification, and the impact of time allocation as well as data issues impacting the project timeline. The benefits of collaboration with process experts and the potential for further development in terms via workshop collaborations and creating dashboards is mentioned.

AI Summary and Sentiment Score

The conversation between the researcher and the analyst (respondent) revolves around the challenges and complexities of process mining, data integration, scripting, and data processing in this project involving the QPR platform. There is discussion about the importance of understanding the processes, ownership of scripts, and the difficulties faced in working with data. The challenges of data loading and transformation, consuming data from SAP, and the benefits of using an Oracle database are mentioned. The conversation highlights the need for efficient data transformation, clear communication regarding data handling, and security measures. The speakers also touch on the impact of the data transformation stage on a pricing and project perspective, as well as the limitations and potential of using the QPR tool. Overall, the conversation emphasizes the importance of involving experts, iterative development, and involving various teams in the process.



AI was utilised in analysing the sentiment score, it resulted as 6 because the conversation seemed to be focused on discussing process mining and its benefits and drawbacks. While there are no explicit positive or negative statements, the overall tone of the conversation appears to be neutral and informative. Some statements express satisfaction and appreciation for certain aspects of the project, while others mention difficulties and challenges. Overall, the sentiment is slightly positive. The text contains a lot of technical jargon and discussions about processes and platforms. There is no clear indication of positive or negative emotions in the text. The conversation seems to be neutral overall. There are no strong positive or negative emotions expressed in the text. The text consists of a conversation discussing technical details and project progress. There is no strong positive or negative sentiment expressed. The conversation seems to be discussing technical issues and challenges related to scripting and data security. While there are some mentions of potential errors and concerns overall, the tone of the conversation is neutral to slightly positive. The text consists of a conversation discussing technical details and project timelines. There is no strong positive or negative sentiment expressed in the text. The text contains a mix of positive and negative statements. Some statements express frustration and limitations, while others suggest potential improvements and benefits. Overall, the sentiment is slightly positive. The conversation seems to be discussing various aspects of a process, such as data mapping, invoicing, integration errors, and process mining. While there are some positive mentions of the invoicing platform being neat and efficient, there are also mentions of challenges and difficulties in the process. Overall, the sentiment seems to be neutral to slightly positive. The text contains a mix of positive and negative statements. There are statements expressing uncertainty and lack of knowledge, which can be seen as slightly negative. However, there are also statements indicating willingness to gather more information and positive remarks about the person being discussed.

Further noted in the interview, as a reference, were the QPR scripts links:

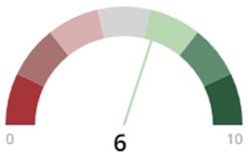
- https://wiki.onqpr.com/pa/index.php/QPR_ProcessAnalyzer_ScriptLauncher
- https://kb.qpr.com/qpr2019-1/qprscripting.html
- https://kb.qpr.com/qpr2022-1/appendixaexamplescripts.html

Appendix 5. Interview (PP 13.6.2024 9–10am) Summary

Key points:

- Process mining is a powerful tool for analysing processes and identifying bottlenecks.
- The project confirmed the impact of increasing self-approval limits and revealed potential for future analysis.
- Sharing the tool with accounts payable could help identify bottlenecks in the invoicing process.
- The interviewee learned the importance of time management and being proactive.
- QPR helped in loading historical data and building dashboards.
- Recommends involving experts from the process mining company and promoting QPR within the organization.
- The lack of up-to-date data was a bottleneck, although this was later solved.
- The project ensured data accuracy and did not mention any specific constraints.
- The speaker suggests considering dedicated resources and involving QPR more proactively.
- They also emphasize the need for internal promotion and training.

AI Summary and Sentiment Score



AI was utilised in analysing the sentiment score, the user discusses the benefits of process mining, such as the ability to analyse the whole process and identify bottlenecks. They also mention the drawbacks, such as the need for dedicated resources and the challenges of obtaining approval for process changes. Overall, the user expresses a positive sentiment towards process mining but acknowledges the limitations and areas for improvement. Therefore, the sentiment score is 7, indicating a generally positive sentiment. The sentiment score is 7 because the text contains positive words such as 'helping', 'motivated', 'open', 'great', 'useful', 'powerful', 'potential for improvement', 'helpful'. However, there are also some neutral and negative words such as 'mindful', 'not working', 'challenge', 'discussions', 'intention'. Overall, the positive words outweigh the negative and neutral words, resulting in a positive sentiment score. On one hand, there are positive mentions such as the interest in promoting the tool, the correct data verification process, and the potential savings from implementing ideas and changes. On the other hand, there are negative mentions such as the lack of resources, the slow progress due to limited expertise, and the need for more proactive involvement from the tool provider. Overall, the sentiment score is neutral to slightly positive. The sentiment score is 6 because the text contains a mix of positive and negative statements. The speaker mentions positive experiences such as being able to provide information quickly and making team members happy. However, there are also negative aspects mentioned such as the need for more promotion and training, uncertainty about data quality, and the need for guidance from project leaders. Overall, the sentiment is slightly positive due to the positive experiences mentioned, but there are also concerns and areas for improvement mentioned.

Appendix 6. Interview (AS 20.6.2024 10:30–11:30am) Summary

Key points:

Decision Making in Modelling:

- Modelling can be done independently or by the tool provider, each with pros and cons
- Tool provider: Fast results, straightforward and easy-to-read models
- Self-doing: More time-consuming but considers company-specific customizations and exceptions, leading to more trustworthy results

Process Mining Benefits:

- Provides a good overview of processes, showing actual performance versus planned
- Useful for auditing, identifying well-performing areas and areas needing improvement
- Helps in benchmarking and knowledge sharing

Challenges in Process Mining:

- Data accessibility issues, especially with data stored in different systems
- Missing data elements like timestamps can hinder analysis
- False positives can occur, requiring careful interpretation

Tool Selection and ROI:

- Important to carefully investigate different process mining products due to price and experience variations
- ROI is more evident in business use cases than in auditing

Implementation and Use:

- Combining self-made models with professional help can ensure technical correctness and reduce delays

- Dashboards are crucial for presenting data to management; they should be professional and user-friendly
- Regular involvement of external partners like QPR can keep the project on track

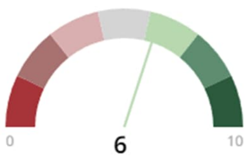
Project Management:
- Clear objectives and data requirements should be established at the beginning
- Iterative approach is often necessary as new data needs are discovered
- Time allocation and involvement of external partners can help maintain progress

Training and Usability:
- QPR's training materials need updating to reflect the new environment, Snowflake
- Usability of the tool is important; initial user experience can impact adoption
- Regular updates and communication about new features are essential

Feedback and Improvements:
- Continuous feedback to tool providers like QPR can help improve their products and support
- Regular webinars and better documentation can enhance user experience and knowledge

The key points summarise the main ideas and considerations discussed in the interview regarding process mining, platform selection, implementation, and project management.

AI Summary and Sentiment Score



AI was utilised in analysing the sentiment score, the text provides a balanced view of the pros and cons of process mining and the use of specific tools like QPR. It highlights positive aspects such as improved process visibility, audit efficiency, satisfaction with the QPR tool, appreciation for the team's knowledge and enthusiasm, and the belief that process mining can be beneficial. However, it also mentions drawbacks like data accessibility issues, the challenge of detecting fraud, disappointment with unrealistic expectations, challenges with data handling, concerns about dashboard usability, outdated training materials, slow progress, and poor usability compared to other tools. The overall tone is informative and slightly positive, reflecting cautious optimism about the benefits of process mining, but also acknowledges significant frustrations and dissatisfaction.

Appendix 7. Interview Themes

Table 2. QPR Process Mining Experience.

QPR Process Mining Experience	
Senior Analyst	More of a concept for experts to understand their processes better – gives insight, confirmation, and clarity on the magnitude of how often cases and events occur. Benefits in granularity levels and real case exceptions in the process can be identified which is good for enhancing. It is rare for experts to find totally new things as they often suspect issues and know their processes well, plus they select the filters and criteria on the data. Alternative perspectives are possible though. The main drawback is the reliance on data quality, as this dictates the process mining end results.
Team Leader	A powerful tool for analysing data and improving processes. Having a technical background and a dedicated team can enhance the effectiveness of process mining. We have been able to analyse bottlenecks and make improvements with the help of data brought into the tool. The importance of data in making business cases and obtaining approval for process changes from management was emphasized. With more resources and time, we could achieve even greater benefits from the QPR process mining tool. Identifying how to improve processes is useful, especially considering we are analysing just one part of the P2P process. It is not like we do not know our bottlenecks, or what to improve, but more to confirm these areas and the impact. To approve change, we need confirmation, and I think this tool has helped us a lot in business cases, preparation and improving our assumptions with the data because based on experience, sometimes experience and assumptions is not enough to receive approval to projects for example, because there are financial risks involved which we should accept.
Audit Analytics Manager	There are pros and cons of process modelling done independently versus by a tool provider. Independent modelling is more time-consuming but allows for customization, detailed understanding and trust in the data being correct when it comes to company specific processes and there is a possibility to make changes in the data if required. However, provider-made models are faster and easier to read but may lack transparency, although technical/syntactical professional support is valuable. A combined approach is suggested for optimal results. Process mining offers valuable insights for auditing and business overall by showing how processes operate, providing evidence and benchmarking opportunities. For businesses the data is also pinpointing values and process steps as opposed to opinions and guessing, it is therefore efficient to show the data directly as it is clear - false positives may arise at times though. Main challenges include data accessibility and completeness, especially when data is spread across different systems or lacks necessary elements such as timestamps.

Table 3. Project Objectives.

Project Objectives	
Senior Analyst	Could have been clearer from the start, as these were more set on a general level. Getting started with process mining focuses more on the data capturing, the analyst involvement was too deep in the operative process therefore we had to query our management on the approach. This was a new thing for us, so adjustments were applied to the original plan.
Team Leader	We, as a project team, did not know what to expect from the tool, what it could bring us and how fast results would be. The technical part took quite a lot, but the general objective was to analyse the whole process, to understand bottlenecks and to see if our development ideas were tackling these bottlenecks – to confirm we were moving in the right direction, also discovering something new would have been welcomed. Keeping in mind that it took close to one year with fetching old data in the tool and then to have results I think was pretty much enough as an objective. Also, making sure the data was correct, testing the data, plus adjusting it when necessary.
Audit Analytics Manager	I acted more as a consultant and supported the Senior Analyst with transforming the data into QPR. The benefits of process mining for identifying inefficiencies were highlighted, citing an example from the P2P process where manual changes to payment terms were identified as wasteful. Process mining can help improve processes and provide data-driven insights for decision-making. I think that QPR can be beneficial, as I can a lot of waste in processes. My latest example within the P2P process was when I made a PO regarding [x], there was 2 days difference between the payment terms. One person went into the purchase order and manually changed the payment term, I thought if this is something frequent then what a waste. If you can obtain what kind of waste there are in the process from the process mining tool then you can start improving the process, I really believe that it will be beneficial and you can actually show someone who is making decisions that ‘look here is the amount of hours we are spending with this activity and this is how much it costs’, as no one can argue against the data. Further, as a remark on a similar previous project objective, the QPR tool was intended for detecting fraud. Whilst the tool can identify irregularities, it requires significant process knowledge to interpret the data correctly, leading to some disappointment from Audit management as there were somewhat unrealistic expectations on catching fraudulent cases.

Table 4. ROI Calculations & Business Case.

ROI Calculations & Business Case	
Team Leader	The QPR process mining tool will not free our time, it is not meant for this, management needed to accept that. However, based on development assumptions before, we now have the business case data where it has been confirmed afterwards that there is this return on investment. We will be able to analyse after projects are up and running. Calculating and estimating the numbers based on QPR analysis is clear and our assumptions were very accurate (only one hour difference from assumed versus actual time saved after analysis). Even if the start in Process Mining was slow, it has started to pay off now, so we will see even more by year end.
Audit Analytics Manager	Investing in process mining is worthwhile, but it's important to carefully compare different products due to price and experience variations. The decision to use QPR in the company's auditing function was made before I joined the company, focusing more on compliance than ROI. The main goal was to automate control points in processes like Purchase-to-Pay (P2P). The tool helped in auditing by providing a dashboard to monitor process performance, making it easier to identify areas needing attention. Overall, QPR has been beneficial for auditing by simplifying the review process and providing clear insights.

Table 5. How the Project went.

How the Project went	
Senior Analyst	The QPR platform has been utilised, but there were challenges in understanding and transforming the data. Loading data from Coupa and SAP was not always straightforward, and the script building process required greater expertise than anticipated. The SQL editor in Snowflake was easy to use, but verifying the data and checking for errors was time-consuming. The project faced delays due to lack of time allocation and issues with the data. QPR software was good, but there were concerns about the dashboards. Security was assumed to be in place due to this already being established and our company has an existing partnership, but more clarification could have been provided to give peace of mind. Understanding the logic and building the model in process mining took time. Testing and converting scripts also caused delays. Overall, more collaboration with process experts and workshops would have enhanced the experience and made the data more actionable.
Team Leader	We were active with this project after the summer last year, the main challenge was that we have a lot of work on our tables, and this was a side project. Focusing on QPR was difficult as we attempted this internally. We did a lot of tests and findings, then the model was necessary to change e.g. the case ID was required to be adjusted to get the data connected correctly. We were dependant on others before any analysis could have been possible. We should have used QPR's support more, because as soon as the license was about to expire, they became active in supporting us (cleaning up the model, the loading of the historic data and Coupa data). They also supported in making the dashboards and in general supporting us and encouraging us to know how to get the most benefits out of the tool. We had consultant services from QPR (5 days) was included in the initial package; we were heavily supported towards the expiration of the license. Project Manager support was important and somewhat missing in the initial stage, we mostly used the consultancy for data cleanup towards the end. They have most experience with other companies and could have shared more information and findings. They know how to organise the process mining and more guidance in the start would have been good.
Audit Analytics Manager	The project team demonstrated impressive experience and knowledge, particularly in technical and process areas. The importance of having experts who understand the process in detail was highlighted, as this ensures accurate model building, and avoids false positives. The team's enthusiasm, good questions, and overall competence were highly praised.

Table 6. Project Limitations.

Limitations	
Senior Analyst	The platform's user interface and dashboards are not so familiar to me, the overall idea with root-cause analysis, bottlenecks, etc. are possibilities but I have not been using the tool much. I see that it can be a bit difficult to dig into the details of the data, as there are data limits on what we can extract [e.g. in terms of comments in the Coupa system to support the data]. The tool is broad and capable, but I am not sure if there is some data that is still missing/required to transform.
Team Leader	Lack of resources were a limitation for our project, we must manage our expectations from our project. Of course, QPR knows how to sell their product and use examples and arguments to its maximum capabilities, however, with personnel never doing Process Mining before does have an impact on our outcomes, in addition to this being a side project and not our full-time job. Therefore, the results are not to their maximum but limited. If we would have dedicated resources and full-time focus, then the results would be much broader and faster. Either, one data analytic/mining personnel, experts on the process, one project manager, one change management manager owning the tool, and the process mining provider also provide a faster turnaround. In the spring there was an example of a process mining project in Kone, although they used another process mining tool, they had a dedicated project and full-time resources allocated to the project, so naturally leading the change and therefore the results were also more impressive as they had more resources allocated to this project. We cannot compare to this as our set up is smaller and we take more baby-steps. We focus on our department now and only one other team has used process mining so far, however, there is a potential that the rest of our organisation would adopt this – we must share the knowledge.
Audit Analytics Manager	Lack of data for some part of a process, or if we don't have any access/easy access to the data, this can be very complicated. Particularly free-text fields in data analytics as these fields can be difficult to process due to their variability and length, making it hard to extract valuable information. AI tools like Copilot have been tested but often provide incorrect information, so caution is advised when using AI for analytics. AI might offer some support, but it is not yet reliable enough for critical tasks.

Table 7. Recommendations & Lessons Learnt.

Recommendations & Lessons Learnt	
Senior Analyst	If the project would be started from scratch, a quicker/easier approach, would be to have heavy and successful sprints and workshops, this would be ideal to ensure licenses are utilised and data is ready for testing. The possibility for turnaround for the process experts to review would also be beneficial. Having data stored in multiple platforms (in our case SAP & Coupa) data mapping is super important. I would recommend having one platform with the full End-to-End (E2E) process [as obtaining data and timestamps is clearer this way], with more than one platform businesses face integration issues which impact the data mining quality. From my personal view, versions and “nice to see” features would not be considered at the same point. The point would be to split these into steps. E.g. 1) development side 2) data usage. A core team would have been ideal to review other parts of the E2E process.
Team Leader	QPR process mining is a very powerful tool to replace PowerBi, dashboards and reports, it could be utilised by many departments and not only our department. Analysing bottlenecks, inefficiencies in the process, automation opportunities, audit queries, etc [are possible]. A helicopter view and long-term view would be using the tool for real-time analysis would provide such a potential for improvement and can be a platform for discussing ways of working. Trainings for all departments on how to use QPR would be huge, replacing existing tools with something new can face challenges. For us, for now, we can continue to utilise it to confirm our ideas and development project business cases. Promoting this tool to Accounts Payable for their part of the process would be beneficial for our Indirect Procurement process too as this is connected to our E2E process with regards to invoice handling, approving, releasing, etc. Further, promoting this within our IP organisation (e.g. in Strategic Purchasing), as more requests to create dashboards, and onboarding them to share knowledge internally so they would be able to utilise the tool too. The most important part is to have someone in the team with an analytics background and if that person(s) would have process mining experience this would be great. The process experts would need to be involved to test and provide feedback along the data transforming part. QPR representatives should be more proactive and available to share more knowledge and support networking with other companies using their tool, this would be great as we were chasing them for support. We will discuss openly and summarise the project together with QPR and finalise the lessons learnt both and provide feedback too. Further, it is important to consider where the tool should land within an organisation, such as in a change management team, rather than an operative team. Lessons learned also include the need for promotion and training of the tool, and the importance of data quality.
Audit Analytics Manager	The project started well with the use of QPR but faced challenges due to a bottleneck; the Analyst was the only one capable of scripting. It was suggested to utilise more support from QPR. The project lacked initial clarity on required data, leading to iterative development. Concerns were raised about the flexibility and potential overwhelming nature of QPR dashboards, emphasising the importance of professional and user-friendly dashboards for management appeal and decision-making opportunities.

Table 8. Other Remarks.

Other Remarks	
Team Leader	A development that was ongoing during our QPR project was said to save our process time, however, this was not the case and process mining data allowed us to refer to the numbers. It was unexpected and very good as now we can prove good development ideas and focus on those since the data can be tested and the impact awareness is greater. Mainly seeing how a development will impact and hopefully in positive ways so we are able to analyse and have these are future goals and sharing the tool with our other teams in the E2E process would be beneficial too, if they can dedicate some time to process mining. Especially e.g. with Accounts Payable as the invoicing part of the process is something that can be a great topic for continuous improvement. This is a part of the process where bottlenecks are evident, and we do not know what the reasons are since we are not process experts in their process. We do not know what is bringing them additional workload, their experts would need to analyse their data. The data in QPR will be up to date soon, as we reach the end of ETL. We know how to do this more frequently and have data refreshed faster. The BPMN model would be ideal to proceed with next, as this would support in compliance queries. Until this moment the main priority has been the transformation of the data and the last stages of this are now happening.
Audit Analytics Manager	QPR and UiPath tools were compared, noting that whilst QPR offers a good product at a reasonable price, it lacks user-friendliness and effective training materials. UiPath, on the other hand, focuses on user experience, making it easier for new users to adopt but less flexible for customisation. It is suggested that QPR should improve its training materials, marketing efforts, and communication about product updates. Product releases occur every six weeks, it is proposed that QPR could have half-hour webinars to highlight main changes and improvements, as in the past. A recent experience related to this issue was when a useful but unknown feature for sorting by timestamps while creating a dashboard. Thus, emphasising that improvements are being made but users are often unaware. QPR have a wiki, however, finding information is sometimes difficult. This should also be improved to enhance the user experience and webinars could keep people on board. Such feedback would be good when wrapping up this project.

Appendix 8. Project Timeline

May-June	June-December	June-August	October-February	March
• Pre-study • Topic planning & meetings • Training on the tool	• License to tool • Workshops verifying the transformed data	• Material collection • Pre-data analysis	• Data analysis • Thesis writing • Proofreading & meetings	• Deadline

License to QPR ProcessAnalyzer 1.6.2024 – 31.12.2024

15.5.2024 QPR meeting – SAP P2P data model is transformed until 2023, the Coupa data model is also transformed until 2023, and there are 5 dashboards based on the 2023 data.

Steps completed:

- Average PR processing time based on 2023 data
- Purchase order price changes after invoice entry
- Root causes for PO price changes after the invoice
- Unnecessary manual work for orders with value of maximum 150 euros
- Payment blocks for framework orders
- Add 2024 data and update the model on a regular basis
- Coupa data model imported to 2024
- Coupa history data to be fetched to analyse rework precisely
- New dashboards as per management and other teams' request

Future steps:

- Future, involve other teams in IP (SPs, CMs) and in P2P (AP)