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The value of process mining in strategic-decision making.

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ABSTRACT

Process mining is becoming a popular big data analytics and artificial intelligence tool in business today as a result of technological advancements being accelerated by digitalization. Fast process adaptation to keep up with the pace of the quickly evolving business environment, however, is a significant challenge for the majority of organisations. Process mining has the potential to make big data-driven insights accessible, transforming data mining into a process mining capability therefore raising the value of process mining. Additionally, process mining insights give businesses the ability to improve and optimise processes to gain a competitive advantage. However, the value of process mining in organisational strategic decision-making is underexplored; this study aimed to fill this research gap.

A qualitative research design was adopted to explore new insights and answer three research questions. This study put forward the exploratory design using the philosophy of interpretivism and the inductive approach to developing new theory. Semi-structured interviews with eleven participants who have implemented process mining were conducted to gain further insights into this phenomenon.

With respect to the value of process mining this research found benefits that include better decision making, cost savings, business process transparency and enhancement of business processes through automation. However, organisations still need to rely on human intelligence and expert intelligence to get value from process mining. On the context of how organisations get value from process mining four main stages of process mining implementation were found in this study. The steps identified include: planning, data extraction and processing, mining and analysis, and process improvement. With respect to the value of process mining in strategic decision-making, this study found process mining to be applicable in this context while providing some examples. Generally, the findings of this study contribute to the extant literature related to process mining.

KEY WORDS

Process Mining, Strategic-decision making, dynamic capabilities, artificial intelligence, big data, automation

ABBREVIATIONS

AI – Artificial Intelligence

BI – Business intelligence

BDA – Big Data Analytics

CEO – Chief Executive Officer

DDD – Data Driven Decision

RBV – Resource Based View

RPA – Robotic Process Automation

TQM – Total Quality Management

DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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1. CHAPTER ONE: INTRODUCTION TO RESEARCH PROBLEM

1.1 Introduction and Background

Organisations operate in dynamic business environments where the speed and astuteness with which dynamic capabilities such as strategic decision-making are employed are critical to their survival (Mikalef & Pateli, 2017). In this era of digitisation and digitalisation, process mining is an emerging technology that rapidly, and at scale, analyses business processes to support in decision-making as highlighted by various literature throughout the years (van der Aalst, 2012; Park & Kang, 2016; Zerbino et al., 2018; Grisold et al., 2021; Faizan et al., 2021).

As a big data analytics technique that maps end-to-end business processes, process mining is gaining momentum in today's business environment (Grisold et al., 2021). For example, Celonis, a commercial software company, recorded an increase in net worth from 2.5 billion at the end of 2019 to 11.1 billion US dollars in June 2021 (Konrad, 2021). This 344% gain in net worth in less than two years demonstrates the practical utility of process mining in today's volatile and uncertain business environment. Furthermore, Grisold et al. (2020) assert that process mining has provided value to hundreds of organisations worldwide hence it is a developing area of study, particularly from a business application context.

The growth of process mining is fuelled by three major factors. The first is that dynamic markets force organisations to adapt quickly to changes in the business environment for survival (Haarhaus & Liening, 2020). Therefore, organisations must swiftly optimise business processes to ensure competitive advantage and improved performance (Albino, 2021). It is becoming increasingly vital for organisations to become agile in decision-making by utilising the knowledge they have to define their strategic direction ((Jeble et al., 2017). Although making such decisions is difficult in the face of uncertainty, process mining technologies can help to augment decision-making (Eggers et al., 2021).

Given shifting consumer expectations organisations which can adjust swiftly are able to better take advantage of the opportunities and mitigate the risks in the business environment (Mikalef & Pateli, 2017). While conventional aspects of business success remain important, traditional approach is insufficient to sustain growth in dynamic and internationally competitive marketplaces (Yeow, 2018). Therefore, many organisations in different industries are embracing new technologies to help enhance capabilities such as strategic decision-making (Faizan et al., 2020) with process mining, being such a technology.

The second driver of the growth of process mining is that as information systems become more widely utilised, more data is accessible for use in process mining (Markus, 2017; Graafmans et al., 2021). Organisations are able to uncover process deviations for improvement using process mining which automatically compares actual processes to ideal process models (Eggers et al., 2021). Process mining's capability to discover real processes in organisations has aided companies such as BMW, Uber, SAP, Ernst & Young, Airbus, and Vodafone in process automation, auditing compliance, and business process optimisation (Grisold et al., 2020). Consequently, this rise in data-driven decision making has paved way for process mining to be integrated into business process analysis and optimisation in organisations (Wamba & Mishra, 2017a).

However, the complexity of the strategic decision-making process in organisations has increased due to the development of big data, the diversity of information systems, and data formats both inside and outside of organisations (Intezari & Gressel, 2017). Unfortunately, decision-making is sometimes fraught with ambiguity, uncertainty and risks; and decisions made are based on assumptions framed from individuals or team knowledge and experience, and values and beliefs (Leyer & Schneider, 2021). Fortunately, the large volume of big data plays a crucial role in augmenting strategic decision-making, and should not be overlooked (Intezari & Gressel, 2017). Therefore, process mining as an emerging technology that provides insights from data is becoming increasingly relevant in today's business environment.

The third driver of the growth of process mining is the declining efficiency and effectiveness of the traditional business intelligence (BI) tools. These tools such as total quality management (TQM) and six sigma strive to optimise business processes by lowering processing time and mistakes (Graafmans et al.; 2021). However, because these traditional BI tools analyse manually acquired data, the related high costs and slow recovery of results makes them unsuitable in this fast-changing business environment (Graafmans et al., 2021). Another key issue is the traditional BI tools are further hampered in ability to analyse complicated processes with high variability (Kregel et al., 2021), thus presenting process mining as a preferable solution. In brief, while the conventional BI tools are still useful, they fall short in assisting organisations in dynamic and internationally competitive environments (Kregel et al., 2021).

Ultimately, an organisation's performance is determined by its ability to make timely and high-quality decisions (Alhawamdeh & Alsmairat, 2019). Given the three levels of decision-making: strategic, tactical, and operational, this study concentrates on the use of process mining in strategic decision-making (Özemre & Kabadurmus, 2020). Such decisions give long-term direction for an organisation as a whole and specify key goals. Recognising that well formulated strategic decisions enable organisations to gain competitive advantage (Intezari & Gressel, 2017), the goal of this research was to evaluate the value of process mining in strategic decision-making specifically.

Additionally, complexity in strategic decision-making is fuelled by dynamic markets, which demand decision-making agility (Intezari & Gressel, 2017). Remarkably, research has found that artificial intelligence (AI) and machine learning boost the efficiency and quality of strategic decision making in organisations; process mining uses both technologies (Nieto et al., 2019). Furthermore, Eisenhardt and Martin (2000) introduced the notion that strategic decision-making is a dynamic capability that enables organisations to make decisions that lead to performance improvement. The outcome of strategic decision-making is therefore critical, as it determines the organisation's longevity. Moreover, CEOs from America's major firms selected AI and machine learning as the factors that will have the biggest impact on the future of business (Jarrahi, 2018). In addition, 85% of CEOs surveyed by Accenture in 2017 anticipate to spend expansively in AI-related technology in the next couple of years (Jarrahi, 2018).

This discussion has highlighted that the turbulent business environment, increase in big data, and the gaps from traditional BI tools are leading businesses to process mining as an emerging technology to aid in process analysis and performance improvement. In addition, the market is expected to grow tenfold (Eggers et al., 2021) while the algorithms being used are constantly improving from a technical standpoint (van der Aalst, 2020). It is expected that process mining, as a new BI technique that bridges the gaps from traditional BI tools, will gain traction in organisations. This opens up new avenues for research both from a business and academic context.

1.2 Research Problem

Organisations are under constant competitive pressure; strategic decision-making agility is essential for survival and growth (Mikalef & Pateli, 2017). Fortunately, in this modern digital era, process mining is a novel approach that can swiftly and at scale analyse complicated business processes across multiple information systems and organisations (Zerbino et al., 2018; Grisold et al., 2021; Faizan et al., 2021). Despite the fact that several studies on process mining have been undertaken, empirical evidence of process mining from a strategic viewpoint has not been fully explored (Grisold et al., 2021). Furthermore, minimal attention has been paid to the value and application of process mining in the business context (Faizan et al., 2021), demonstrating that exploration of value in process mining for strategic decision-making in organisations is needed.

1.3 The Purpose of the Study

1.3.1 The study's relevance to business

This study investigates process mining with a view to fill gaps in knowledge on the application of process mining in organisations (Zerbino et al., 2021). Similarly, Thiede et al. (2018) state that most of the research has not examined process mining from an organisational standpoint; a context within which process mining is still in its infancy (Thiede et al., 2018). While there has been extensive research on the invention and enhancement of algorithms, studies on the use of process mining in businesses remain scarce (Faizan et al., 2021). Martin et al. (2021) draw the conclusion that process mining has fallen short of expectations and emphasise the need for further methodological guidelines that organisations might use. Given that prior research has given little focus to understanding how organisations generate value from process mining, there is a lack of awareness of the advantages and limitations of process mining in particular in organisations (vom Brocke et al., 2021).

This points to lack of understanding about the applicability of process mining in business.

In a focus group study of process managers, Grisold et al. (2021) observed that these leaders did not know how to use process mining to gain value for their organisations. Specifically, the participants reported inability to quantify the benefit of process mining. As a result, convincing senior decision-makers, such as board members, to invest in process mining becomes challenging (Grisold et al., 2021). While some studies have concentrated on the advantages of process mining, it is unknown how these benefits relate to increased income and lower operating costs in organisations (Martin et al., 2021). As a result, more real-world research, as urged by Zerbino et al. (2021), will help organisations learn how to apply process mining.

Despite substantial research on the technical facets of process mining, researchers have not thoroughly addressed the application of such insights (Martin et al., 2021). Scholars have examined process mining from a computer science perspective leaving several potential business applications unattended (Zerbino et al., 2021). Furthermore, the use of process mining to improve operational, tactical, and strategic decision-making has been pushed to the margins. For example, investigation into how managers could utilise process mining to make strategic decisions remains limited (Zerbino et al., 2021). In general, process mining research has largely ignored organisational needs (Grisold et al., 2021), emphasising the need for empirical exploration.

1.3.2 The study's relevance to theory

Zerbino et al. (2021) observe that conference papers on process mining outweigh journal publications despite the poor scientific impact of conference papers. Additional evidence that further research is required is provided by Thiede et al. (2018) observation that process mining research is still in its infancy. As process mining is a new and developing field of research, there is a paucity of expertise on how organisations can utilise process mining to gain significant insights (Eggers & Hein, 2020). Furthermore, research has lacked understanding of the underlying causes and processes that enable organisations to deploy process mining to extract significant insights. Additionally, a majority of the studies have been descriptive in nature, focusing on the technological aspects of using process mining (Grisold et al., 2021). Moreover, even though organisational practises and capabilities are used to implement process mining, it is not completely known how antecedents affect the application of process mining (Eggers & Hein, 2020). By focusing on process mining from an organisational position, this research contributes to academic discourse on the issue.

1.4 Conclusion

Technological advancement, accelerated by digitalisation, is accelerating the application of process mining in organisations (Eggers et al., 2021). However, a major difficulty for most organisations is quickly adapting processes to match the pace of the rapidly changing business environment (Eggers & Hein, 2020). Process mining holds potential to unlock access to big data-driven insights that advance data mining into process mining competency, increasing the value of process mining (Corallo et al., 2020). Moreover, process mining insights enable organisations to enhance and optimise operations. However, the utility of process mining in driving strategic decision-making from an organisational standpoint is under explored; a research gap that this study attends (Zerbino et al., 2021).

1.5 A synopsis of the rest of the document

Chapter 2 describes the theoretical foundations of process mining and presents the dynamic capabilities theory and the strategic decision-making concepts. The review also pursues discussion on process mining as a strategic decision-making facilitator.
Chapter 3 outlines the research methodology and design used to collect and analyse empirical data that attends to the research questions.
Chapter 4 details the findings.
Chapter 5 presents discussion from the data and links it to theory.
Chapter 6 concludes the report by detailing the implications to business and limitations of the study that can aid future research.

2 CHAPTER TWO: LITERATURE REVIEW

2.1 Introduction

This section investigates three major concepts, namely process mining, strategic decision-making, and dynamic capabilities. The discussion serves to expound on context relevant to the research questions and aims established in chapter one. The section begins by outlining the key ideas before delving into how process mining and strategic decision-making relate as dynamic capabilities that could give organisations a competitive advantage. Aspects of research carried out on process mining and the gaps in knowledge that remain to be filled, conclude the scene setting.

2.2 Processes Mining

The process mining agenda gained momentum in 2011, with the publishing and formalisation of the process mining manifesto led by professor Wil van der Aalst and other task force members (van der Aalst et al., 2012). The manifesto has since been utilised for study by various researchers. There are numerous definitions of process mining; one recently coined by Zerbino et al. (2021) refers to process mining as a collection of data-driven methodologies for diagnosing and optimising business processes by merging machine learning with business process management. Several academics (Thiede et al., 2018; Corallo et al., 2020; Grisold et al., 2020; Eggers & Hein, 2020; Graafmans et al., 2021; Martin et al., 2021) agree with this definition with small variations. This has widened agreement on the concept and scope of process mining as a new technology for improving business processes.

Process mining is pursued along three streams, process discovery, compliance, and enhancement (Thiede et al., 2018). The first, process discovery, is the most well-known; it generates process models without the use of any prior information (Martin et al., 2021). This is often harnessed by new businesses or contexts that do not have processes documented. In established organisations, process discovery yields a mapping of actual organisational processes based on data recorded in information systems.

Process conformance compares the actual process model to an ideal model (Martin et al., 2021). Conformance checking is used to determine whether or not actual processes, as documented in information systems, adhere to the ideal model supplied by the organisation, and vice versa. This often reveals deviations from what practitioners believe to be set process. Furthermore, rules like the Sarbanes-Oxley Act (SOX) and the Basel II Accord highlight the importance of compliance (Martin et al., 2021). Process mining approaches enable more transparent compliance checks, verifying the validity and dependability of organisations fundamental processes (Van Der Aalst et al., 2012).

The third category is enhancement, which assesses numerous processes and recommends the best model based on business impact (Martin et al., 2021). The purpose here is to use data from actual processes collected to enhance or enhance an existing organisational process. By including timestamps, for example, the process model may be enhanced to illustrate bottlenecks and throughput times (van Der Aalst et al., 2012). According to literature, process enhancement has received least attention, despite the fact that it has the potential to provide meaningful insights (Faizan et al., 2021).

Finally, process mining tackles four distinct perspectives: process, organisation, time, and case (Zerbino et al., 2021). Process perspective orders relevant activities; time attends to the timing and frequency of activities; case pertains to analysis of situations based on particular qualities and finally organisation examines who performs what and how they are networked (van Der Aalst et al., 2012). This organisational perspective demonstrates the social network and in this way, process mining can assist managers in making strategic decisions such as restructuring activities or allocating long-term resources (Dakic et al., 2018). It is worth noting that the process and case views have received most attention in research, whereas the time and organisational perspectives are not well attended (Zerbino et al., 2021). The type and perspective of process mining to be employed by the organisation is determined by the business objective, which might be process automation, compliance, or business process improvement (Grisold et al., 2020).

2.2.1 The evolution of process mining

According to Eggers and Hein (2020), the notion of automatically generating process models from information systems of previous processes executed was established in 1985. Since that time, process mining has emerged as a technique for identifying, monitoring, and enhancing actual business processes in various industries (Faizan et al., 2021). The cornerstone for process mining is data which shows the activities related to a process in the information system utilised by an organisation (van der Aalst, 2020).

Process mining emerged due to concerns that, traditional business intelligence (BI) technologies and management practises like six sigma and TQM that seek to lower processing times and errors; are not efficient in increasingly volatile business environments (Graafmans et al., 2021). Traditional BI tools analyse manually acquired data, making these tools expensive and time-consuming to use (Graafmans et al., 2021). Furthermore, reliance on expertise of persons participating in an analysis, result in subjectivity through personal experiences and perspectives. Using the traditional tools also poses a challenge in capturing complexity and variety in processes (Graafmans et al., 2021).

Enormous volumes of data are being recorded and stored by modern information systems and devices. Event data, in particular, gives records of previous operational activities, allowing process mining to map these processes (Graafmans et al., 2021). Furthermore, unlike traditional BI tools, when process mining is utilised, the same analysis may be replicated in the organisation at reduced cost (Park & Kang, 2016). This enhanced capability closes the gap in business process analysis performed by traditional BI tools (Dakic et al., 2019). The use of data mining techniques to automatically produce process models that are compatible with dynamic behaviour is acknowledged as having emerged through process mining as process mining compares the new versus established processes, uncovering deviations (Dakic et al., 2019).

2.2.2 Process Mining Applications and Benefits

Various benefits of process mining have been documented in literature. For example, Jarrahi (2018) highlights that process mining enhances decision-making efficacy, resulting in faster decision-making and better outcomes. Furthermore, according to research, process mining has achieved a variety of goals, including assisting organisations in comprehending prevailing processes and serving as a foundation for process improvement (De Weerdt et al., 2013). More importantly, several scholars emphasise process mining impact on business (Park & Kang, 2016; Zerbino et al., 2018; Faizan et al., 2021). They highlight that this capability enables organisations to examine what actually occurs within operations, such as undesirable steps, bottlenecks, and compliance difficulties. This is accomplished by comparing actual process models to ideal process models while leveraging event data from information systems to identify process deviations and inefficiencies (Zerbino et al., 2021).

Process mining supports digital transformation by revealing improvement potential in critical success characteristics such as efficiency, agility, speed and compliance (Geyer-Klingeberg et al., 2018). It also aids in the detection of solution strategies for example process transformation, human change, or technological shift. Ultimately, organisations are able to select appropriate measures for strategy execution like automation, user training or system migration to optimise activity synergies (Kretschmer & Khashabi, 2020). This is realised by making mechanisation levels in the organisation transparent enabling users to rapidly and easily evaluate the maturity of business processes and discover greatest potential (Leno et al., 2021).

However, it is not clear how management generates improvement action plans to remedy identified process inefficiencies based on new insights from process mining; this highlights a gap in existing research (Faizan et al., 2021). The benefits and challenges of using process mining in businesses are not widely known (Martin et al., 2021). As caution, van der Aalst (2020) observes that, although performance management in organisations impacts the present and future, process mining is backward-looking as it analyses events of past actions. However, it can be argued that the benefits stem from long-term collaboration with distinct human talents (Jarrahi, 2018). Therefore, rather than concentrating on short-term achievements, establishing the economic value requires patience and a long-term vision (Jarrahi, 2018).

Given these challenges, the requirement for return on investment (ROI) calculations to measure immediate financial impact of process mining can be discouraging

(Jarrahi, 2018). This means that considering and treating it as a solution to all problems in the organisation is not advisable. Relatedly, decades of study have shown that organisations are complex sociotechnical systems, and technology advancements can only succeed if carefully incorporated into an organisation's social fibres (Jarrahi, 2018); process mining is no exception.

2.2.3 PM requirements and building blocks for implementation

Organisational practises that foster the implementation and utilisation of process mining must be in place. The adoption of process mining requires a well-defined strategy, project management, and the availability of analytical talent (Eggers & Hein, 2020). Importantly, senior management must support the efforts and provide resources required to execute the project (Eggers & Hein, 2020).

According to Graafmans et al. (2021) the four stages of process mining implementation are as follows: planning, data extraction and processing, mining and analysis, evaluation and process improvement support. The business goals and questions are developed during the planning phase (Aguirre et al., 2017). A project team is formed after selecting the processes to be analysed and improved. Prior to data analysis, it is crucial to develop precise business goals and questions the organisation expects process mining to address (Graafmans et al., 2021). The most difficult part of the planning step is selecting which actions must be documented for example task repetitions, such as a mouse click, may be relevant or insignificant in a given context (Leno et al., 2021).

The second stage entails data collection where data from information systems is collected and processed to generate clear, filtered, and enhanced event logs supported by confirmation of data correctness and quality (Graafmans et al., 2021). Because the cornerstone for process mining is event data captured in information systems, the emergence of BDA techniques necessitates the development of data analytics capabilities in the organisation (Janssen et al., 2017). Noteworthy, understanding the aim of the analysis is more crucial than gathering and processing data to construct process models and evaluate results (Leno et al., 2021). This is why the first phase of planning is important. A key issue at the second stage is distinguishing noise from events that contribute to tasks, due to unpredictability and variations in data quality (Leno et al., 2021).

The third step of data mining and analysis involves a thorough review of the data by the team under the direction of the process analyst with the goal of identifying potential root causes for problems identified in the first stage (Aguirre et al., 2017). This allows for the framing of improvement opportunities that can be implemented in the subsequent stage (Graafmans et al., 2021).

In the final stage, process mining is used in recognising potential impact of various improvements and selecting those likely to have greatest business impact (van Eck et al., 2015). The organisation analyses if impact of the enhancements represents desired results and whether processes have been successfully enhanced (Graafmans et al., 2021). The business user serves as the improvement project's leader and is in charge of overseeing the performance indicators to see if process modifications generate the desired results (van Eck et al., 2015). It is only then that the business can report on the success of utilising process mining in the organisation.

2.3 Decision-Making

The decision-making and management processes are intertwined (Fleig et al., 2018). Making decisions is critical to what managers do and is intricately tied to all areas of management (Intezari & Pauleen, 2018). Furthermore, an organisation's performance is determined by its ability to make timely and high-quality decisions (Schoemaker & Day, 2021). There are, however, several types of decisions. This section presents a framework for examining organisational decision-making. In 1965, Robert Anthony defined three stages of decision-making that were strongly related with levels of managerial responsibility (Anthony, 1965; Edwards et al., 2000; Zhang et al., 2015;). These levels dubbed strategic planning, management control, and operational control, have been renamed to strategic, tactical, and operational decision-making (Pereira et al.,2020).

Strategic decisions give long-term direction for decision-making (Alhawamdeh & Alsmairat, 2019). This highlights the entrepreneurial side of management in organisations, when, for example, shifting to a related sector of operation is undertaken. Strategic decisions are perceived as unstructured because of the variety of possible actions, the need for information from outside sources, and the use of criteria based on overall company ambitions rather than specific organisational problems (Zhang et al., 2015).

Tactical decision-making on the other hand, translates strategic goals into targets and operating criteria (Pereira et al.,2020). Tactical decisions define boundaries set by the strategic decisions made, and hence decisions at this level tend to be more organised (Zhang et al., 2015). Finally, operational decisions necessitate choices at the activity control level. These decisions are even more detailed and limited in scope, focusing on directing the day-to-day operations of a given division in light of strategic objectives (Alhawamdeh & Alsmairat, 2019). These decisions are more organised, relying mostly on information sources within the company (Pereira et al.,2020).

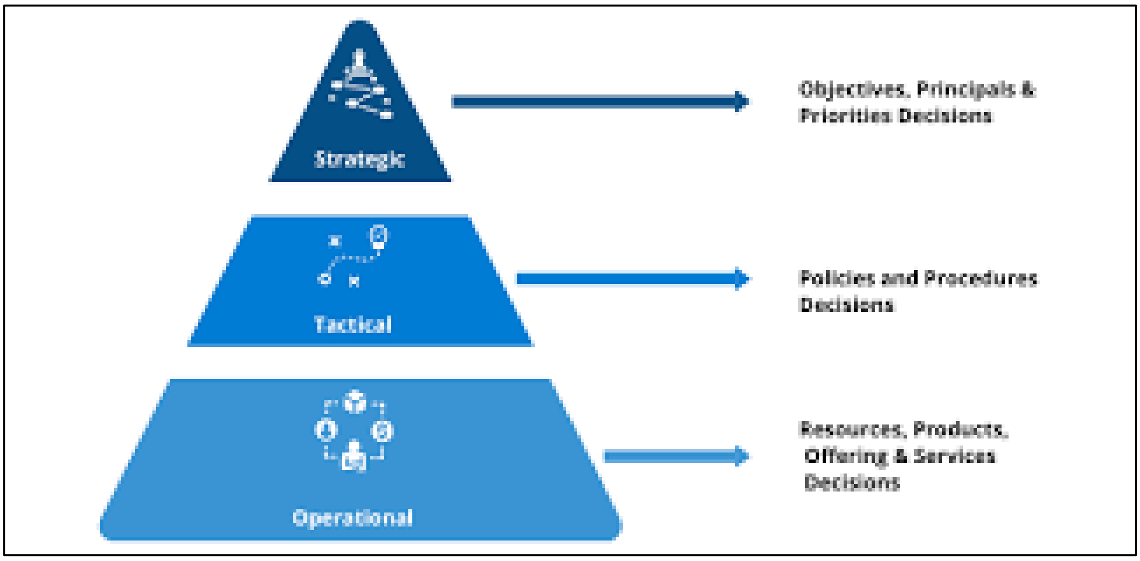


Figure 1: Decision making levels

There are numerous typologies of organisational decisions. Structured and unstructured decisions are widely accepted categorises based on complexity (Jeble et al., 2017). Accordingly, an organisation's decision-making process may be structured or unstructured. Structured decision-making is seen as a sequential or orderly process (Intezari & Gressel, 2017). On the other hand, although traditional mathematical models such as statistical approaches and linear programming can depict structured decisions, there is no widely acknowledged method for offering ideal solutions to unstructured problems (Zhang et al., 2015). A good decision, is made by an executive through systematic approach containing elements that are well defined and in a predetermined order (Intezari & Gressel, 2017).

The Cynefin framework shows another method for constructing decisions depending on context (Intezari & Gressel, 2017; Ilieva et al., 2018; Shalbafan et al., 2018). The framework defines five settings if no other context is appropriate: simple, complicated, complex, chaotic, and disorderly (Intezari & Gressel, 2017). These distinct scenarios are distinguished by the cause-and-effect relationship or lack thereof.

Simple and complicated settings have causality links, but complex and chaotic events are unique and unexpected (Intezari & Gressel, 2017). As a result, simple and complex situations may be likened to structured decisions, which need managers to categorise the issue at hand and, in certain circumstances, employ analysis to discover the correct response (Ilieva et al., 2018). On the other hand, complex and chaotic occurrences might be viewed as unstructured decisions that can only be evaluated retrospectively for response correctness (Kravchenko & Shevgunov, 2022). In order to reach meaningful and viable findings, decision-making requires dynamism and agility. Therefore, the rate at which decisions are made is directly related to organisational performance (Alhawamdeh & Alsmairat, 2019).

2.3.1 Strategic Decision-Making

Whilst cognisant of the separation of decision-making levels: strategic, tactical, and operational, this research concentrates on the use of process mining for strategic decision-making. Research shows that process mining can aid in both tactical and operational decision-making; however, it is outstanding strategic decisions that enable organisations to become industry leaders by gaining competitive advantage. According to Intezari and Gressel (2017) an organisation's success or failure is mostly decided by capacity to navigate competitive environment.

Eisenhardt and Zbaracki (1992) provided an early definition of strategic decision-making, stating that it is a complex social process that draws on different stakeholder contributions to choices and trade-offs that the organisation must make. Complexity, process, and choice are three critical elements in this definition, and reliable data is critical to support effectiveness (Intezari and Gressel, 2017). This is why process mining, that employs big data analytics and AI technologies to create important insights (Carillo, 2017; Leyer & Schneider, 2021), requires additional investigation to evaluate its value in assisting organisations with strategic decision-making.

Eisenhardt and Martin (2000) propose that strategic decision-making is a dynamic capability that allows organisations to make choices that lead to a competitive advantage. Relatedly, Grisold et al. (2020a) use the example of LOEN Entertainment (Pty) Ltd to demonstrate the value of process mining in business. This South Korean media company employed process mining insights to segment customers and develop new services (Grisold et al. 2020a). This is an example of how process mining can support strategic decisions that lead to competitive advantage. Therefore, further research on the value of process mining in strategic decision-making is required to equip organisations with a road map for implementation (Zerbino et al., 2021).

In conclusion, decision-making tasks vary in characteristics, and as a result, are approached in a number of ways (Lu et al., 2019). Judgements can range from day-to-day operational choices to long-term strategic corporate options; from single internal decisions to multi-level or multi-organisational consideration (Pereira et al.,2020). Ultimately, solutions must be found through a process of uncovering and evaluating choices before selecting optimal options; being the most gratifying solutions to the problem at hand. This is where the improvement and evaluation phase of process mining is beneficial as it guides evaluation of the impact of various decisions on business performance before selecting the best option to implement (Zerbino et al., 2021).

2.4 Process Mining and Strategic Decision-Making

2.4.1 Process mining: Big Data decision-making technique

The practise of making decisions based on data analysis rather than intuition is referred to as data-driven decision-making (DDD) (Smith, 2017; Lu et al., 2019). Research shows that, even after accounting for wide range of potentially perplexing aspects, the more data-driven an organisation is, the more productive (Özemre &

Kabadurmus, 2020). Moreover, the gains are significant: one standard deviation improvement on DDD results in approximately 6% boost in productivity (Lu et al., 2019). DDD appears to be causally related to greater ROA, ROE, asset utilisation, and market value (Lu et al., 2019). There is substantial evidence that data-driven decision-making is beneficial since it improves organisational performance dramatically (Jeble et al., 2017). Therefore, an organisation's capacity to process data has influence on its performance (Janssen et al., 2017).

Strategic decisions involve a high level of uncertainty, ambiguity, and risk therefore, acquiring, analysing, and evaluating credible data and information is vital (Lu et al., 2019). Big data is viewed as an opportunity by academics and practitioners to get new insights, better decision-making, and gain competitive edge (Özemre & Kabadurmus, 2020). Organisations can profit from big data's most noticeable properties, namely volume, velocity, and diversity, given the correct technology and adequate expertise (Janssen et al., 2017). This is because its analysis allows businesses to move quickly, adjust processes, and improve customer experiences (Lu et al., 2019).

Big data expedites decision-making, reduces cost and improves outcomes (Janssen et al., 2017). Increasing volume, diversity, and velocity of information, together with falling data and database costs, can assist enterprises in making improved strategic decisions (Özemre & Kabadurmus, 2020). Big data and advanced analytics provide value through increasing transparency, frequent performance feedback and enhanced objectivity in approach therefore using big data can yield effective strategic decision-making and implementation (Intezari & Gressel, 2017).

Data, in simpler and more organised forms, has been utilised to assist in decision-making and business processes in more conventional activities such as BI and analytics since the 1950s (Wamba & Mishra, 2017). The principal purpose of big data exploration is to support in making real-time decisions by enabling managers to obtain insights from a variety of data sources, outperforming traditional methodologies on which organisations historically relied (Intezari & Gressel, 2017). These capabilities aid in quick capture, processing, and analysis of data. Data-driven decision-making also enables automated decision-making based on data engineering and storage technologies (Lu et al., 2019). However, previous research on data utilisation indicates that quality impacts outcomes. The superiority of the data may impact the standard of decisions (Wamba & Mishra, 2017).

Academia and practitioners are increasingly interested in the area of big data. Big Data Analytics (BDA) assists organisations in gaining insights that revolutionise end-to-end processes, sharpening competitive advantage (Jeble et al., 2017). Organisations may augment decisions through successful use of BDA to boost efficiency and quality of operations by using effective business process management (Duan et al., 2019). BDA and business process integration can successfully result in the creation of new economic assets, allowing organisations to reinvent their strategic positioning and surpass competitors (Wamba & Mishra, 2017). BDA offers enormous potential for altering different organisations and sectors in search of long-term competitive advantage (Jeble et al., 2017).

While much has been written about BDA's impact at operational and strategic levels, empirical evidence of true economic benefit at the organisational level is lacking (Sun et al., 2018). On the other hand, the link between BDA and process innovation, remains scant (Wamba et al., 2017). This is why process mining as a technique that uses big data analytics is important to study, to understand potential for innovation and improvement.

Moreover, the exploration in the field of big data and cognitive computing is still in infancy (Gupta et al., 2018). There are concerns that the quantity of data is set to become unsustainable, necessitating use of computer systems to help humans in making decisions (Gupta et al., 2018). Processing huge amounts of data is a difficult undertaking for organisations (Janssen et al., 2017). A cognitive system processes raw data and turns it into actionable knowledge; making the process scalable, as well as time and effort saving (Gupta et al., 2018).

2.4.2 Process Mining: Artificial Intelligence (AI) technique for Decision-Making

AI is defined by Duan et al. (2019 p.2) as "the capacity of a computer to learn from experience, adjust to new inputs, and execute human-like activities." According to Jarrahi (2018), AI may be defined broadly, as intelligent systems that can think and learn. Big Data's availability and power is revitalising AI as technologies rapidly evolve, for example increased computational storage capacity and super-fast data processing technology (Leyer & Schneider, 2021). The current generation of AI technology has improved capacity to create predictions based on data whilst cutting forecasting costs (Jarrahi, 2018). There are few academic research publications concentrating on comprehending usage and influence of future generation AI from the perspective of supplementing human decision-making (Duan et al., 2019). Evidently, the study of process mining as a technique that uses AI to help in strategic decision-making is relevant.

The use of AI can be examined from the strategic, tactical, and operational decision-making levels (Leyer & Schneider, 2021). Duan et al. (2019) assert that although AI is effective in operational and tactical decision-making, it falls short in strategic decision-making. The role of AI systems in decision-making is also investigated in terms of decision structure; either structured, semi-structured, and unstructured (Leyer & Schneider, 2021; Kravchenko & Shevgunov, 2022). AI may be used for organised or semi-structured decision-making, but is best employed in organisations to support tool with unstructured decisions (Kravchenko & Shevgunov, 2022).

Markus (2017) highlights that AI should be used in areas where humans fall short, such as contact centre operations, driving and certain judgement skills. Similarly, jobs that are difficult to perform, such as detecting patterns in massive amounts of unstructured multidimensional data (Markus, 2017). In the latter case, process mining is used to map patterns from enormous volumes of data that humans are unable to perceive (Fiazan et al., 2021). Nonetheless, due to algorithm capacity, AI should not be applied to particular jobs, such as judgement tasks, unless, during the operation and advancement of algorithms humans are kept in the loop at all times (Jarrahi, 2018). Notably, AI research should seek information concerning real strategic decisions on task automation; determine why these decisions are made; assess repercussions and developments over time (Nieto et al., 2019).

AI has evolved as a credible tool for supporting, and potentially replacing, human decision-makers (Jarrahi, 2018). In contrast, AI technology can process large volume of data at rapid speeds and with wide spectrum of reason (Duan et al., 2019). Decision-making and accepting responsibility for the repercussions of those choices are key managerial actions as management careers depend on ability to make sound judgements that affect business performance (Alhawamdeh & Alsmairat, 2019). In the abstract, decision-making is challenging; humans must also deal with their own conscious and unconscious prejudices (Leyer & Schneider, 2021). This condition typically leads to bad decisions, which have negative impact on performance. The complexity of decision-making, along with humans' limited rationality and the necessity of decision-making for organisational performance, explains a long history of academic and business interest in how AI might aid decision-making (Smith et al., 2017; Leyer & Schneider, 2021).

However, even AI, does not attain total rationality (Gonzalez, 2017). Technology is not fully devoid of prejudice; for example, programmers cannot be completely unbiased when developing an algorithm (Jarrahi, 2018). Furthermore, the scope of AI's challenges is broad, including political, social, economic, ethical, and legal concerns as well as organisational and administrative (Leyer & Schneider, 2021). The majority of AI applications have focused on operational duties like facial recognition or market analysis, with only a few organisations utilising AI's potential to assist management roles like strategic decision-making (Leyer & Schneider, 2021). One issue is that, little is known about the interactions between people and AI, despite the fact that AI-powered software helps organisations augment strategic decision-making (Leyer & Schneider, 2021). Therefore research on process mining as an AI enabled technology is relevant.

2.4.3 Process mining: Dynamic capability for strategic decision-making

2.4.3.1 Dynamic Capabilities

Pursuing exploration of process mining through a dynamic capabilities lens is appropriate. Teece et al. (1997) presented initial thoughts on organisational agility to integrate, develop, and reconfigure capabilities to deal with rapidly changing business situations. Barney et al. (2001) later characterised dynamic capabilities as the unique mechanisms through which organisations leverage resources to gain competitive advantage. However, there is a shortage of research on how organisations may use information technology enabled dynamic capabilities to add value to organisations making long-term decisions that impact strategic direction (Mikalef & Pateli, 2017; Faizan et al. 2021; Albino, 2021). This highlights the relevance of studying process mining as an IT enabled dynamic capability.

Eisenhardt and Martin (2000) also as early scholars of dynamic capabilities mention that using dynamic capabilities to adjust to rapidly changing business environments becomes a source of competitive advantage (Haarhaus & Liening, 2020). However, in order for an organisation to maintain prolonged competitive edge, dynamic capabilities must be used in unexpected ways to make strategic decisions ahead of competitors (Mikalef & Pateli, 2017). According to Leyer and Schneider (2021), organisations with strong technical capabilities can augment strategic decision-making. Process mining as an emerging technology improves agility in strategic decision-making (Corallo et al., 2020). This reinforces the need to investigate how process mining might be used to navigate strategic decision-making.

Dynamic capabilities are becoming increasingly important to examine, act, learn, and adapt when confronted by uncertainty. Dynamic capabilities theory is commonly viewed as an extension of the resource-based view (RBV) of the firm (Schilke, 2018); an important strategic management concept for understanding how organisations create and maintain competitive advantage. The RBV focuses on unique resources (tangible and intangible assets), as well as capabilities held by a firm (Haarhaus & Liening, 2020). Whereas ordinary capabilities are required to guarantee that current resources are used efficiently and effectively; dynamic capabilities are described as an organisation's ability to actively create, extend, or transform its resource base (Laaksonen & Peltoniemi, 2018).

Moreover, dynamic capabilities, as Teece (2014) highlights are especially significant in high-velocity situations as ordinary capabilities are only sufficient in stable environments. In light of rising turbulence and unpredictability, the dynamic capabilities theory has received more attention as an enabler of competitive advantage, a primary goal of strategic management (Salvato & Vassolo, 2018). With enhanced competencies, organisations can adapt core competencies to undertake strategic changes in response to environmental changes (Haarhaus & Liening, 2020).

Despite agreement among scholars that volatile conditions necessitate robust dynamic capabilities, the theory has been criticised for providing a limited perspective (Arndt et al., 2022). Various literature have advanced the Teece 1997 original concept of dynamic capabilities resulting in a number of alternative theoretical processes (Salvato & Vassolo, 2018; Haarhaus & Liening, 2020; Arndt et al., 2022). However, further examination of the underlying activities and functions are needed to comprehend the antecedents of dynamic capabilities. In particular, the importance of sensing, seizing and reconfiguring strategic focus ahead of competition requires attention (Haarhaus & Liening, 2020).

Furthermore, the dynamic capabilities theory is said to have no practical consequences for day-to-day management (Arndt et al., 2022). In light of the theory's limitations in providing viable strategies for managing volatility and uncertainty, Haarhaus and Liening (2020) advocate merging dynamic capacities theory with strategic foresight research. Connecting these research streams might reveal new knowledge on how businesses can prosper in volatile and competitive environments (Haarhaus & Liening, 2020).

Figure 2 depicts the relationship between the three constructs of process mining, strategic decision-making, and dynamic capabilities. Aguirre et al. (2017) developed a process mining implementation methodology that includes planning, data extraction, data processing, evaluation, and process improvement and support. When compared, process mining phases are similar to the decision-making procedures mooted by Leyer and Schneider (2021) of identifying goals, obtaining information, evaluating choices, implementing decisions, and ultimately analysing results. This demonstrates how process mining may be integrated into decision-making processes; it provides opportunity for empirical research (De Weerdt et al., 2013). Furthermore, a dynamic capabilities lens allows the researcher to investigate the research topic using the three streams of capabilities: sensing, seizing, and reconfiguring (Teece, 2014).

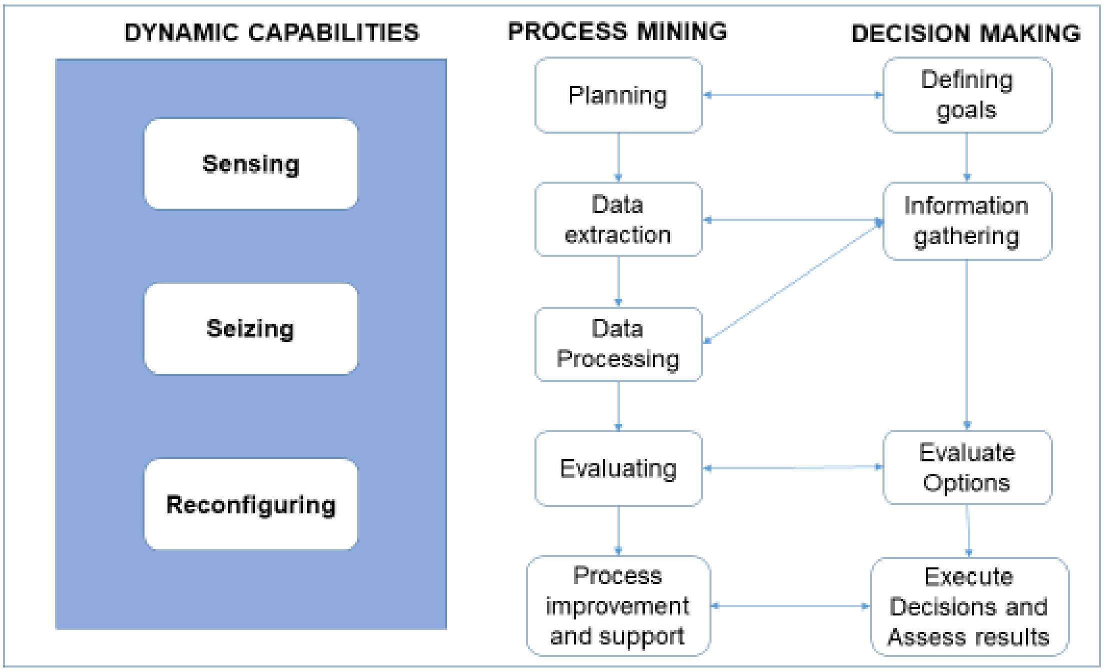


Figure 2: Diagram illustrating the relationship between process mining and decision-making phases.

Sensing

It is crucial for organisations to monitor market activity, gaining knowledge on strategic positioning opportunities (Mikalef & Pateli, 2017). This market scanning may be done throughout the process mining planning and data extraction phases, as the organisation generates business inquiries and acquires information both internally and externally (Teece, 2014, Yeow et al., 2018; Aguirre et al., 2017). Market intelligence must be timely and accurate in order to be valuable for strategic decisions about their consumers and rivals (Yeow et al., 2018; Albino, 2021). Decision makers can swiftly scan the environment and obtain important information through process mining, guiding the use of internal and external competencies to create competitive edge (Mikalef & Pateli, 2017). Organisations can recognise creative market opportunities when they have strong sense-making capabilities and a reliable early warning system. It is also helpful for approaching risks in a timely way; a vital organisational competency for survival in volatile business environments (Haarhaus & Liening, 2020).

Seizing

Market surveillance paves way for an organisation to capitalise on possibilities presented by the business environment while mitigating risks to survive (Yeow et al., 2018). This involves, in part, organising activities and resources to eliminate redundancy and enhance successful cooperation (Mikalef & Pateli, 2017). Process mining reveals realised business processes and identifies dysfunctionality that contributes to strategic blind spots (Grisold et al., 2020). This enhancement in granular insight strengthens objective data-driven decision-making (Eggers et al., 2021). In turn, new opportunities require strong capabilities to create, appraise, and rapidly set direction to adapt to changing needs (Haarhaus & Liening, 2020).

Reconfiguring

Reconfiguration refers to an organisation's ability to action strategic decisions (Mikalef & Pateli, 2017). One of the most common difficulties for managers is to swiftly execute strategic decisions in order to capitalise on fast changing opportunities (Mikalef & Pateli, 2017). Process mining can assist in analysing the outcomes of actions made by the organisation throughout process improvement and support phases (Aguirre et al., 2017). Furthermore, using the organisational viewpoint of process mining, which looks at who does what and how they are networked (Zerbino et al., 2021), process mining may help gain competitive edge through restructuring or pragmatic resource allocation (Cummings eta al., 2020). Finally, for long-term profitable growth, organisations need reconfiguration capabilities that allow technology to progress and adjust to environmental changes through rearranging of resources and organisational structures (Haarhaus & Liening, 2020).

2.5 Conclusion

Advancements in big data, algorithms, and more computer power and storage have elevated the significance of process mining capability for organisational decision-making (Lu et al., 2019). Consequently, there is a growing need for researchers to examine the implications of process mining on decision-making; contributing to progress in theory and practice for process mining application (Duan et al., 2019).

The range of data sources and formats that have emerged both inside and outside of organisations has made strategic decision-making processes more difficult (Jeble et al., 2017). Strategic decisions are frequently ambiguous, unpredictable, and risky since they are founded on individuals and teams assumptions, experiences and perceptions (Smith, 2017). Meanwhile, the diversity, velocity and volume of big data can be positioned to inform and improve strategic decisions, and should not be overlooked (Intezari & Gressel, 2017).

With the present technical rate of progress emphasised by digitalisation and digital transformations, process mining has emerged as a key to unlocking organisational success (Kretschmer & Khashabi, 2020). The insights gained from data reveal opportunity to enhance and optimise business processes (Duan et al., 2019). The path to such achievement, however, is fraught with obstacles ranging from lack of awareness on how to strategically implement process mining (Zerbino et al., 2021). Organisations who are battling to deploy process mining are missing out on AI technologies to augment decision-making, leading to a competitive advantage ((Leyer & Schneider, 2021).

The relevance of process mining in a data-driven world, its fundamental aspects, and its importance in providing competitive advantage were all emphasised in this literature analysis. In addition, the problems and contemporary advancements in process mining were described, revealing symbiotic interaction between process mining and decision-making.

3 CHAPTER THREE: RESEARCH QUESTIONS

3.1 Introduction

This chapter discusses the key research questions that will be addressed in this project. Research questions are developed in response to the gaps identified in the literature evaluation in Chapter 2.

3.2 Research Questions

Although scholars have pursued research on process mining, the approach has been biased towards technical specifications; business application environment has received less attention (Martin et al, 2020). A review of one hundred and forty five research publications on process mining and organisation management by Zerbino et al. (2021) supports this concern. The need to examine the value of process mining to organisations has grown in importance and urgency. Moreover, Grisold et al. (2020a) suggest that future study should investigate the organisational implications of process mining. Relatedly, the first and second research questions for this study are as follows:

Research Question 1: What is the value of process mining in organisations?

Research Question 2: How do organisations generate value from process mining (Grisold et al., 2021)?

Furthermore, according to Thiede et al. (2018), additional empirical study is needed to evaluate the relevance and effectiveness of process mining in strategic decision-making. This was highlighted as one of eleven gaps clouding scholarly insight into process mining by Zerbino et al. (2021). Process mining's strategic contributions include how insights might assist in making long-term decisions such as restructuring and resource allocation (van der Aalst, 2012; Cummings et al., 2020). However, considering that workflow system event data is mostly operational, process mining is more effective with operational choices (Zerbino et al., 2021). In contrast, van der Aalst (2012) claims that process mining may be used in strategic decision-making.

How to optimize this requires deeper investigation; leading to the third research question for this study.

> **Research Question 3:** What is the value of process mining in driving strategic-decision making in organisations?

3.3 Conclusion

The literature review emphasised the necessity of process mining in a data-driven world, as well as its potential to bring value to strategic decision-making capabilities. Despite numerous studies on process mining, little is known about how organisations might utilise it for strategic decision-making (Zerbino et al., 2021). Research indicates a lack of awareness of how organisations might use process mining as a dynamic capability. These insights influenced the research questions selected for this study.

As big data makes process mining increasingly common (Markus, 2017; Duan et al., 2019), this study examines the value of process mining for decision-making and contribute to theoretical and business application progress in this field. This study pursues a qualitative design in addressing the questions. Data was collected through in-depth semi-structured interviews with process improvement professionals that have applied process mining.

4 CHAPTER FOUR: RESEARCH METHODOLOGY

4.1 Introduction

The methods and approach used to address the study questions outlined in chapter three are described in this chapter. A qualitative approach was employed to investigate process mining from experienced professionals to obtain rich insights into the value or process mining in strategic decision-making. Semi-structured interviews with eleven participants were used to gather the data. Following that, the information was coded and categorised in accordance with the themes identified in the literature review, which is detailed in chapter two.

While developing the research methodology and while collecting and analysing the data, potential issues with data validity and dependability were taken into consideration. The researcher's time and resources were taken into consideration when developing and implementing strategies to mitigate these concerns. At the conclusion of this chapter, ethical issues are discussed and presented alongside the study's limitations.

4.2 Research Design

Zerbino et al. (2021) state that no empirical studies have been found looking at process mining from a purely strategic lens. Thus, the research design was exploratory allowing the researcher to discover and gain insights into the value of process mining in strategic decision-making (Saunders & Lewis, 2018). The exploratory nature of the study was ideal for this relatively understudied research area as notably, scholars such as Grisold et al. (2020) performed an exploratory study using focus groups and Martin et al. (2021) also performed an exploratory study using the Delphi method to determine the opportunities and challenges of process mining in organisations. Such studies, however, are far in between and further emphasise the need for more exploratory research in this area to uncover new insights.

According to Basias and Pollalis (2018), the philosophy of interpretivism, which is generally associated with qualitative research, was used in this study. First, interpretivism was appropriate for this research as previous studies focusing on the technical aspects of process mining adopted a positivist philosophy (Zerbino et al.,

2021) while this study will focus on the business application lens. Additionally, Basias and Pollalis (2018) advised that for an in-depth analysis of different variables like technology, people and organisations, the flexibility of interpretivism is valuable. Equally important, Saunders and Lewis (2018) argue that interpretivism supports the multi-perspectives of participants given their experiences add to the richness of data collected. Finally, Martin et al. (2021) and Grisold et al. (2020) used interpretivism in their research by talking to focus groups and using the Delphi method.

During the course of this research, both deductive and inductive methods were used. Prior to conducting the investigation, pertinent, current theoretical notions from the field of process mining were initially found. The researcher was cognisant of these concepts during the designing of the interview schedule. This is a deductive research approach, according to Azungah (2018), because theoretical ideas influenced the evidence that was gathered. In order to identify themes that emerged during the examination of the qualitative data, the study then employed an inductive methodology. The inductive approach is considered to be more adaptive and offers a better understanding of the study context and the importance of actions in the field (Azungah, 2018). The inductive methodology shed light on process mining experts' experiences and the value of process mining in strategic decision-making. This allowed the researcher to discover new knowledge and develop a theoretical understanding from data which is ideal in understudied areas according to Woo (2017).

A mono-method qualitative methodology was used in this study. Qualitative method was selected since the research aim was to uncover rich, meaningful insights into the value of process mining in strategic decision-making (Saunders & Lewis, 2018). Azungah (2018) stated that qualitative research aims to understand the phenomenon, leading to meaningful contextualisation of the research questions as the phenomenon cannot be investigated outside its context. Additionally, Janssen et al. (2017) highlight the use of a qualitative method to develop a thorough understanding of the variables affecting decision-making quality. Moreover, qualitative research's flexibility and open nature led to the uncovering of new knowledge from participants on the concept of process mining from a strategic lens (Gaus, 2017). The Mono-method was appropriate as only a single data collection technique was used given the time constraint (Saunders & Lewis, 2018).

A phenomenological research strategy was considered the most appropriate strategy for this research. Phenomenology as a form of qualitative research whereby the researcher tries to comprehend the experiences of the participants and then uses the data obtained from these experiences to analyse and interpret that information (van Manen, 2017) was ideal. This is more so because, theory thus far does not provide a unified understanding of the value of process mining in strategic decision-making, leaving a gap for more rigorous debate in academia (Zerbino et al., 2021). This study was mainly to better understand this phenomenon, since more organisations are implementing process mining (Grisold et al., 2020). Moreover, with literature providing inadequate insights regarding the value of process mining in strategic decision-making, this phenomenon is poorly understood and valuable lessons for process managers are lost (van Manen, 2017).

Phenomenology allowed for the flexibility required in this qualitative study and was valuable for in-depth empirical data required on this topic by capturing experiences of process mining professionals (van Manen, 2017). Deep understanding was necessary to discover a wide range of aspects influencing decision-making and identify the mechanisms for enhancing decision-making quality (Janssen et al., 2017).

Finally, given time constraints, data were collected at a single point in time in August and September 2022 making it a cross-sectional study (Saunders & Lewis, 2018). Evidently as highlighted by Asiamah et al. (2017) that qualitative research requires the respondents to reason deeply and speak extensively, taking up much time to collect the data. This was evident by most potential participants stating the constraint of time as their main reason to not be able to participate in the study. Thus single time collection was ideal as the researcher was facing time constraints. The research findings are therefore exclusively applicable to this specific time period in 2022, and no generalisations about earlier or later times were made in light of them.

4.3 Research Methodology

4.3.1 Population

The target population with the relevant characteristics for this study were process improvement professionals who have implemented process mining during their career. The characteristic highlighted above is necessary to explore the research area on the value of process mining in strategic decision-making from the perspective of these professionals to answer the research questions (Asiamah et al., 2017). Moreover, the time limit of one year was to ensure the process improvement professionals had used process mining for a considerable period and hence could provide comprehensive insights. Process improvement professionals that did not meet these criteria were not considered as ideal participants for this research and hence were not invited to the interviews.

4.3.2 Unit of analysis

Gaus (2017) explained that the unit of analysis refers to entities from which research requires answers. The unit of analysis for this research was process improvement professionals who have implemented process mining during their career (Guetterman & Fetters, 2018). These ensured that the participants provided valuable and unique insights based on their experience working with process mining.

4.3.3 Sampling method and size

Purposive sampling was used as the sample was selected based on relevance to the study, that is, process improvement professionals who have implemented process mining during their career (Asiamah et al., 2017). Furthermore, Campbell et al. (2020) mention that purposive sampling helps with credibility and conformability of data. The researcher used LinkedIn to find individuals process mining professionals. The initial focus on South Africa as the context only brought minimal results leading to the researcher expanding the scope to include professionals working in the UAE and Germany to improve the richness of data collected.

This type of sampling is non-probability sampling, as the total population of process improvement professionals who have implemented process mining during their career remains unknown. It is in line with Saunders and Lewis (2018), who advocated non-probability sampling as the most suitable sampling method in the absence of a sampling frame. The choice of a homogenous sample is relevant given the purpose of the study allowing for the research problem to be explored in great depth (Berndt, 2020).

The researcher set the parameters with the caveat that interviews would conclude once data saturation had been reached for the specific sample because there are no established guidelines for a sample size in qualitative research (Berndt, 2020). Gill (2020) asserts that when determining the suitability of a sample, the appropriateness of the data collected is just as crucial as the number of participants. The researcher was flexible regarding the size of the sample because the goal was to obtain data with sufficient depth to address the research questions rather than to conduct a certain number of interviews.

4.3.4 Measurement instrument

An interview guide in Appendix 1 was developed and used as a practical measurement tool (Saunders & Lewis, 2018). The research questions were developed based on literature to explore the identified research area. Furthermore, to align the literature reviewed and the research questions, the interview questions were mapped against each research question (Roulston & Choi, 2018). As much as the interview questions were designed to validate the literature, they were kept at a high enough level to prevent leading the participant (Gaus, 2017).

As part of refining the interview guide, the researcher conducted one pilot interview to test the measurement instrument regarding the relevance and understanding of the questions by participants. This process supported with refining the interview questions (Saunders & Lewis, 2018). The pilot interviews also allowed the researcher to adjust the measurement instrument improving the quality of data collected (Majid et al., 2017) for example a preamble was added that the interviewer used in subsequent interviews to create rapport with the respondents.

4.3.5 Data gathering process

Participants were questioned using a list of questions (Appendix 1), but because the interview was semi-structured, the questions' wording were changed at times to fit the situation. The interview had a conversational tone (Brown & Danaher, 2019). The goal of this method was to give informants' spontaneous narratives, which can contain valuable new insights, a controlled level of flexibility. With the participants' consent, the interviewer decided to record the interviews and not to take any comprehensive notes throughout the interview in order to give full attention to the dialogue and interact with the respondent.

Semi-structured interviews were used corresponding to the qualitative research design and research approach selected for this study (Gaus, 2017). Brown and Danaher (2019) note that semi-structured interviews ensure flexibility in the research by allowing adjustments to be made to interview questions based on the insights uncovered, leading to rich findings on the research problem. Given the interpretivism philosophy, the semi-structured interviews allowed the participants to share their experiences based on their perspectives (Basias & Pollalis, 2018).

The interviews were conducted virtually to save on commute time for both the interviewer and interviewee and take advantage of the recording and transcribing capabilities of the current conferencing softwares like Zoom and Microsoft teams. A brief introduction to the research was provided outlining the aim of the study and the general composition of the interview session (Saunders & Lewis, 2018). During the introduction, the interviewer explained to the respondent that their participation was voluntary and their responses would be treated with confidentiality. An indication of the interview duration was provided together with the contact details of the researcher and the supervisor (Basias & Pollalis, 2018). The interviews were recorded, and the audio recordings stored electronically with multiple back-ups to reduce the risk of data loss. These electronic files are password protected to restrict access and to further ensure data confidentiality.

Campbell et al. (2020) assert that depth of data, not frequency, should be used to determine the appropriate sample size for qualitative research. After seven interviews, the data saturation was approaching. Only three new unique replies were found and tagged for further analysis by the seventh interview. After four further interviews were conducted, it was decided to stop collecting data due to saturation and well as time and resource constraints. Therefore, the data collection stage was completed after eleven interviews and no new codes were being generated. This is in line with Berndt (2020) who argued that data should only be collected until no new themes emerge, signalling data saturation, and any further data collection is of little value.

4.3.6 Data Analysis approach

Data obtained was analysed using ATLAS.ti to identify patterns and common themes to answer the research questions (Saunders & Lewis, 2018; Skjott & Korsgaard, 2019). Data analysis was only started after all the interviews were completed largely due to time constraints.

During the data collection process, the audio recordings were provided to a transcriber to support with the transcriptions processes. This decision was made largely due to time constraints on the researchers side and also to help the researcher be removed from the research for some time before analysing the data. After the recordings had been transcribed, the transcriptions were reviewed and respondents names replaced with initials to maintain confidentiality. The transcripts were then uploaded to Atlas ti in a text format to enable any formatting or spelling corrections to be done during the coding process.

The researcher decided to analyse the transcripts using thematic analysis (Terry et al., 2017) before explaining the findings. The process further entailed using Atlas-ti to derive codes and assign code names that best captured the participants' responses (Saldaña, 2014). The evaluation of the theory served as the foundation for creating the initial coding table and further developed as more data was analysed during the coding process (Cresswell, 2014). The codes were then grouped into categories and sub-categories based on how they related and their similarities (Terry et al., 2017). These categories were later organised into themes and assigned a definition highlighting the theory discovered (Saldaña, 2014). Additionally, to prove the trustworthiness of the findings, a frequency analysis, which is a count of the number of participants who provided responses related to certain codes and themes, was performed and documented in chapter five (Terry et al., 2017).

4.3.7 Quality controls

First, to ensure sample validity, respondents selected were vetted on the criteria of having implemented and used process mining in organisations. Respondents that did not meet these criteria were not invited nor allowed to participate (Campbell et al., 2020). Second, to ensure the reliability of the measurement instrument, the interview questions were designed based on the literature (Roulston & Choi, 2018). Nonetheless, they were kept at a high enough level to prevent leading the participant and allow new insights to emerge (Saunders & Lewis, 2018).

Third, to limit researcher bias, one pilot interview was conducted to assess the researcher's influence on participant responses and identify possibly leading questions (Majid et al., 2017). In addition, during the interview, the correctness of the researcher's interpretation of responses was clarified with the interview participants (Saunders & Lewis, 2018). This is because the nature of qualitative studies is that the researcher is intimately involved in every step of the research process and researcher bias is expected (Gaus, 2017). Finally, participants' understanding of interview questions was regularly evaluated during the interview to improve data quality. The interview was recorded, and the recordings transcribed verbatim.

4.3.8 Limitations

First, the online interviews selected for this research did impede body language reading and limit the rapport that would have been created via face to face interviews to enable richer data to be collected (Gray et al., 2020). This was mitigated by following the interview guide provided in Appendix 1 to get both the interviewer and the interviewee relaxed and open for conversation. Additionally, a preamble was include after the pilot interview to introduce the researcher and the research field.

Second, there could be resistance to sharing information about the organisation, which will be mitigated through participants being fully informed regarding the research aims, data storage and usage. Moreover, as Gaus (2017) recommended, the researcher will reiterate anonymity to the research participants to reduce hesitancy.

Third, the inexperience of the interviewer (researcher) might have compromise the quality of the data collection and analysis processes (Basias & Pollalis, 2018). One pilot interview was conducted to reduce the negative impact of the interviewer's experience which allowed the researcher to practice her skills. The critical factor was the researcher's ability to describe and understand the context of the scenario in question to produce new theory (Basias & Pollalis, 2018). Moreover, given the interpretive nature of this study, researcher bias may have limited the data collection, interpretation and analysis as the researcher primarily collected and analysed the data (Gaus, 2017). Various mitigation strategies were employed, for example, ensuring understanding of the participants' responses and recording the interview and transcribing verbatim (Fusch et al., 2018). Fusch,et al. (2018) allude that although bias cannot be eliminated, it can be mitigated in various ways.

4.3.9 Ethical Considerations

The interview technique did not necessitate the assistance of a translator because all participants were English-peaking. Additionally, a consent form was sent ahead of the interview to each participant allowing them time to review before the interview. The signed consent forms were saved electronically. A sample of the consent form has been provided in Appendix 2.

4.4 Conclusion

This chapter presented the proposed research methodology and design for this study. It put forward the exploratory design using the philosophy of interpretivism and the inductive approach to developing new theory using the mono-qualitative method as the most suitable to answer the research questions. Phenomenology strategy was also used to get in-depth insights into the research problem, and due to time constraints, data was only collected at one time.

In methodology, the target population and unit of analysis were provided and explained. Additionally, non-probability and purposive sampling were justified for use to get samples from the population. The design of the interview guide as the measurement instrument was also presented. Semi-structured interviews with eleven participants who have implemented process mining were conducted to gain insights into this phenomenon. The data collected was analysed using ATLAS.ti to develop themes that are used to answer the three research questions developed. Finally, the chapter concluded with a discussion of the quality controls, limitations and possible mitigations to ensure the validity of the research.

5 CHAPTER FIVE: FINDINGS

5.1 Introduction

The fifth chapter covers the important findings of interviews done to achieve the study's objective of determining the value of process mining in strategic decision-making. The chapter covers the findings of 11 interviews performed with the goal of answering the three research questions outlined in chapter three. The section begins with information about the interviewed participants and progresses to a deeper understanding of the context of the interviews. The coding procedure, which included a thematic analysis, is briefly discussed, and the results of each study question are provided, with major themes highlighted.

5.1.1 Interview participants and context

All 11 interviews per Table 1, were conducted virtually either via Zoom or Microsoft Teams depending on the respondents preference. Process improvement professionals with process mining experience were selected for the interviews as they provided insights on their individual experience using process mining. The interviews were conducted in English as interviewees varied in terms of geographical location with three main countries: Germany, UAE and South Africa. The initial scope of the research was South Africa however due to a low maturity of the technology, very few respondents were found leading to expanding of the scope to more mature markets like Germany. The average process mining application experience of the respondents was two years indicating the infancy of the technology and field.

A total of 500 minutes of audio recordings were taken, with the final transcripts totalling 63 192 words. The average interview lasted 45 minutes, and the average transcript length was slightly more than 5 700 words, with the longest interview lasting more than an hour. This amount of time allowed the participants to elaborate on their responses to the questions posed. The interviews were done over an eightweek period utilising a conversation guide produced in advance and provided in Appendix 1.

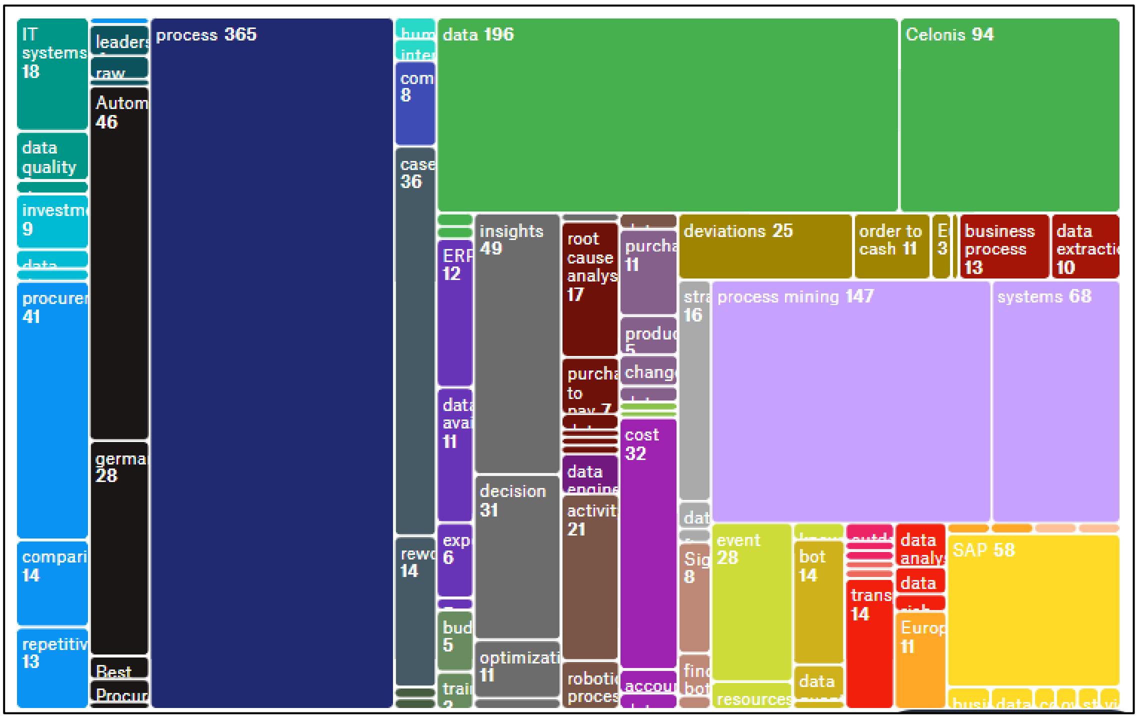
Table 1: Individual Participants

No.	Industry	Geographical Location	Years of Experience	Length (min)	Word Count
1	Consulting	U.A.E	3	32.17	4291
2	Consulting	U.A.E	2	25.32	3087
3	Logistics	Germany	2	54.06	6789
4	Technology	Germany	1	50.04	6418
5	Manufacturing	Germany	2	27.35	5090
6	Technology	Germany	2	47.31	5251
7	Consulting	South Africa	2	65.13	10757
8	e-Commerce	Germany	3	46.21	6457
9	Technology	U.A.E	2	53.25	5471
10	Transport	Germany	3	37.36	4361
11	Financial Services	Germany	1	54.41	5402

5.1.2 Coding Process

The coding process involved coding each transcript in sequence of how the interviews occurred. Once all the transcripts were uploaded in text format on Atlas-ti, the researcher started with coding the first interview. The coding was done line by line where codes were attached to given words, sentences or paragraphs. The initial coding led to 137 codes being created after which codes with the same meaning were further merged for example “automation” “robotic process automation” “bot”. This organising and cleaning was done which led to grouping of the codes. Whenever a new code was created, the researcher would review the previous transcripts to ensure they had not missed that code in those interviews. In very few cases was this found to be true as most new codes created were appearing for the first time in the respective transcript that was being coded. Themes were created from the groups for each research question and will be presented in the rest of this section.

5.1.3 Codes and Code Appearances



Source: Researcher project on Atlas-ti

5.2 General Findings

There are two general findings of this research. First is that of data being the cornerstone of process mining given how many times it was mentioned and second is Celonis appearing as the prominent process mining software.

5.2.1 Data and process mining

During the interviews, the term data was the second most used after the word process. This corresponds to the study focus on process mining as a construct that employs data mining techniques. Table 2 shows the codes used during the analysis to describe the use of data.

Table 2: Codes used for coding “data”

Code		
data: ‘analyse’	data: ‘quality’	data: ‘correctness’
data: ‘extraction’	data: ‘clean’	data: ‘issues’
data: ‘analytics’	data: ‘rich’	data: ‘outdated’
data: ‘raw’	data: ‘engineer’	data: ‘simplicity’
data: ‘financial’	data: ‘transformation’	data: ‘volume’
data: ‘set’	data: ‘ownership’	data: ‘integration’
data: ‘completeness’	data: ‘availability’	data: ‘processing’

Some of the quotes to illuminate on this are provided below:

*"…if you have a solid ERP system that's capturing all the **data** as long as somebody is responsible for driving this in the organization you can get a license."*

*"We probably don't know how big of a problem it is that's where we need **more data** to prioritize solutions for the problems that we have."*

*So what I'll do is I'll **combine** this with the shift **data** and I'll actually see if the no milk situation happened five minutes after the shift.*

Given that data is a key input to process mining, its appearance in conversations further illuminates its importance. However respondents 1 and 11 did not refer to this word as much as the other interviewees in their responses as highlighted in table 3 below:

Table 3: "Data" code per respondent – order by sequence of interviews

	I1	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**	**I11**	**TOTAL**
Data	4	19	5	22	13	17	32	26	23	34	1	**196**

I1 refers to Interview 1, I2 interview 2 and so forth.

Another code to highlight is "insights" given that the output of process mining is insights which are actionable that lead to process improvement. From the data mined, insights are developed that are presented to organisations.

Table 4: "Data" and Insights" code per respondent – order by sequence of interviews

	I1	**I2**	**I3**	**I4**	**I5**	**I6**	**I7**	**I8**	**I9**	**I10**	**I11**	**TOTAL**
Data	4	19	5	22	13	17	32	26	23	34	1	**196**
Insights	11	1	0	1	6	5	2	7	8	0	10	**51**

Interestingly the respondents that mentioned data a lot, minimally referred to the word insights as shown in table 4 above. Upon further investigation and review of I4 and I7 however, it appeared that sometimes respondents used the words data and insights interchangeably. For example in the below quote not verified by the respondents, the word data is used instead of insights as respondents are speaking about the output of process mining, after the data has been mined and analysed.

> *"So we will show you in a tool, in a bubble, to say look there, there's a number of days within a month and we can see that oh …, actually, on weekends there are a lot of people, or few people who are doing this process, transactions …, that they are not supposed to do. So that's one thing that process mining does as well. We can identify if there are users who are doing things that they are not supposed to do. So then as a strategic partner or a person in a strategic position, then you take that* ***data*** *to say actually I always thought my problem is because of this, but these process mining guys, they showed me the root cause of the problem, because as a manager you always see the end of it, to say we always do not get this count, but you don't know why."*

> *"I am able to make better prioritization of problems, better identification of solutions and better monitoring of solutions because I have* ***more data using process mining*** *and* ***more useful data*** *using process mining. That is how process mining really helps…"*

5.2.3 Process mining software tools

There are numerous products and services available on the market right now for extracting business processes, however the word Celonis was the second most mentioned code after data. Celonis is a process mining software provider started in Germany. Only two interviewees did not mentioned Celonis or the process mining software they are familiar with as shown in table 5 below. In comparison to other process mining software providers, Signavio and MPM are not so popular among the respondents interviewed. Celonis stood out as the most used and most known process mining software in this study.

Table 5: “Celonis” “Signavio” and “MPM” codes per respondent – order by sequence of interviews

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	TOTAL
Celonis	11	1	0	11	1	18	38	0	13	1	0	**94**
Signavio	0	0	0	0	0	0	5	0	1	2	0	**8**
MPM	0	0	0	0	0	0	0	0	0	2	0	**2**

> *“We were trying to launch a process mining offering solution in the region, very successful, some pilot projects. We were working with a tool technology partner called* ***Celonis****. Have you come across* ***Celonis****?”*

> *“So we go, get the data analysed, do everything and show the client to say this is how much you can save by using* ***Celonis*** *right…”*

> *“We use* ***Celonis*** *to understand the business today and the processes and that's an adventure to us because otherwise we have, we need a lot of interviews with business owners or process owners…”*

Additionally, the mention of MPM and Signavio was mainly by passing as respondents alluded to not using these softwares but only interacted with the providers from a sales perspective.

> *“And so the topic of process mining came and Celonis came to sell it to us. I don't know if you know Celonis as well* ***Signavio*** *also came to sell it to us but we ended up going with Celonis purely because they're like the market leaders and they were more convincing, I suppose.”*

> *“The second part of a certain role of our team is to provide customers within Deutshe Bahn with licenses for software for example and for another tool which is* ***MPM*** *process mining. MPM stands for* ***MEHRWERK*** *Process Mining, this is a German company and competitor to Celonis or* ***Signavio*** *for example for Signavio is now SAP, for MPM I’m not pretty sure to which company they now belong…”*

5.3 Research Question 1:

What is the value of process mining in organisations?

The purpose of the first research question was to determine the value of process mining in organisations. The interview questions are created to support in the in depth comprehension of the value of process mining. The respondents walked through their experience in process mining , the processes they have used process mining for and the benefits and challenges they have seen from using process mining.

5.3.1 Processes that use Process Mining

Most respondents alluded to the same processes being managed by process mining being procurement-to-pay, order-to-cash and production. These processes were highlighted as the common processes regardless of industry.

Table 6: Code appearance of processes that use process mining

Code	Total number of times code was mentioned
Accounts Payable	1
Accounts Receivable	3
Order to cash	13
Procurement	54
Manufacturing	1
Logistics	1
Production	5

> *"Purchase to pay or **procurement** process is the most demanded, and the most popular process. The second one is order to cash…"*

> *"For example my core area is **procurement** so maybe talk about **procurement** as an example. For example if you're looking at **procurement** you have these cycles like the B2B cycle or even **order-to-cash cycle**. You have that monetary cycle so now using Celonis for any process mining tool from a process mining tool from a decision making like you were saying from a strategic stand point; it gets you a lot of insights"*

Moreover, procure to pay which some referred to us purchase to pay was pointed out as the best process to start within an organisation to get some benefits from process mining.

> *"But the easiest process to start process mining on, are your* ***procure-to-pay*** *processes. So in the case of the procure to pay is not like the core supply chain processes, so the core supply chain are more where we are buying from our suppliers and then getting the stock into our warehouses"*

Other processes that were mentioned include logistics processes, manufacturing, debt-collection, maintenance of infrastructure and assets, accounts payable and accounts receivable processes.

> *"…the biggest demand process of this process mining for us is within maintenance. Maintenance of rolling stock of cranes or for I don't know other vehicles and of course of fix stock, maintenance for example on the infrastructure. So this is the big topic, maintenance and therefore, this is a big part of process mining*

The key finding here is that process mining can be used for a variety or processes and in different industries. The examples spanning from financial sector, to e-commerce to transport and logistics prove that process mining is applicable in any industry as long as processes are involved as mentioned by one of the respondents.

> *"Where there are processes you can always mine them so and if you think they're worth mining them it's then mined..."*

5.3.2 Benefits of Process Mining

It emerged from the respondents that organisations can derive value from using process mining. All respondents confirmed that process mining is valuable to organisations. For example some respondents mentioned that:

> *"Let me give you the top three things about process mining: It's about automation; it's about process improvement; it's about efficiency in the process; and identifying bottlenecks."*

"I think the value generation is pretty clear; you're using something like this it's going to help your bottom line, it's going to make an organisation more efficient, more effective, better turnaround time with the customer, more cost savings for your leadership and it's a win-win situation to use this."

"In terms of value, you've got like effectiveness, better turnaround time, and faster cycle time for your customers, more cost saving for your leadership and also from a controls perspective there is quite a few things like those deviations that I mentioned."

Five key themes emerged on benefits of process mining being enabling cost savings, enabling better decision making, enhancing business process transparency and compliance and finagling enabling business process automation.

5.3.2.1 Enabling better decision-making

In terms of the value of process mining in decision-making, respondents agree that using process mining leads to data-driven decision making which is objective. The capability of process mining to find root causes of problems in the organisations ensures that once a decision is made it seeks to solve the real problem.

*"So based on how I solve a problem all of this I am able to make **better decisions** because I have better data available for me, I am able to make better prioritization of problems, better identification of solutions and better monitoring of solutions because I have more data using process mining and more useful data using process mining. That is how process mining really helps…"*

*"The only thing is that you have an insane amount of data in a structured way which helps you make much **better decisions**, decisions in terms of prioritization, decisions in terms of solutions and decisions in terms of monitoring also."*

*"That's purely because they were able to trust the tool, become a champion of the tool and do it because at the end of the day it's just another tool but it is a very powerful tool which will help you **make decisions much better**."*

5.3.2.2 Enhanced business process transparency

This theme came out strongly through various interviews. Various codes that were used to contribute to this theme are deviations in processes, root cause analysis, process comparison, transparency in processes, compliance to ideal process, finding bottlenecks, conformance and visibility. All these codes contribute to revealing the actual process in the organisation of who does what when and how and how many times increasing transparency of activities.

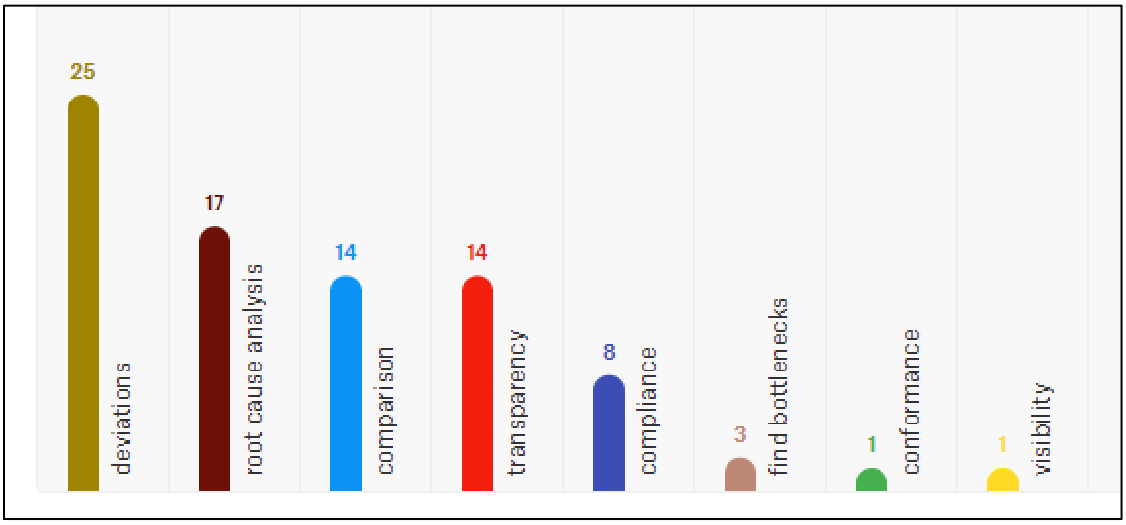


Figure 2: Source researcher project on ATLAS-ti

Some of the quotes that highlight this theme are presented next:

> *"It gives you **transparency** on what happens based on all of the system interactions you have typically."*

> *"It's mostly **transparency**, so the other one effects which are …, so all process mining initiatives are there, say hey we are trying to improve business processes, making them **visible**, **transparent**, making them tangible to people which are connected to the process or process managers or operational people.*

On the other, risks with this levels of transparency in the organisation were also raised as highlighted by below quotes:

> *"So that's why now they can go and say you've done this and the person say no I didn't do it, they say here's the date, here's the time, at this time you did*

this and that and that. So that's the other part that I don't like about it, because it shoots straight to the culprit. To say this is the guy who did this. So that's how we uncover a lot of fraud using process mining. Because you can definitely tell this is the guy, we tell you straight. This is the guy who did it at this time, at this time."

5.3.2.3 Enabling Cost Savings

Enabling costing saving was a recurrent theme with all respondents. There were different ways organisations could attain cost savings either by optimising their processes and making them more lean or by reducing the amount of time used doing certain activities within the processes.

*"So let me structure it more so (1) cost effective, you can **reduce costs**, costs of process (2) can be through automation, we can increase automation, we can analyse what are some business process is the most demanded, where they have lack of resources. What is more repeatable process …, is possible to automate or linearization"*

*"For example I found some problems and inefficiencies and bottlenecks inside their data. I calculated what would be if the company would know about these problems, using process mining and how they will **save money economically** after some changes, digital transformation or organisational changes..."*

*I think the value generation is pretty clear; you're using something like this it's going to help your bottom line, it's going to make an organization more efficient, more effective, better, turnaround time with the customer, **more cost savings** for your leadership and it's a win win situation to use this*

5.3.2.4 Enabling business process automation

Enabling business process automation came out strongly as theme. Process mining was pointed out as a tool that helps to identify opportunities for automation where repetitive work that can be automated becomes highly visible in the organisation.

“…or by the way I totally forgot there is another really good activity that this process mining helps out is when you’ve got the standard process it tells you how many activities or steps in that process is done manually versus in the system.”

“So how much are manual interventions that’s very important. When you see how much of manual interventions are done you can ***automate*** *those processes. That basically shows up another insight called the repetitions. These activities that potentially you can implement some* ***robotic process automation*** *where you can completely remove manual activities and replace that with automation…”*

“So in automation tab we can see all the events, what is the automation rate. Whenever we see cases like…. I don’t know something that is a little bit automated but a huge portion of it is not. That is a message that ***automation*** *is possible but why is it at such a low rate.”*

5.3.3 Challenges of Process Mining

A number of challenges of process mining were raised during the interviews. At the top level, the cost of the process mining tool was quoted to be too high. This is more so because very few process mining tools currently exist in the market and Celonis, which is the most mentioned and used tool is the leader in this market. Respondents alluded to the high cost of the tool being a hindrance to convincing managers and organisations to implement the tool.

“So number one challenge is ***costs****, is a very expensive project. At the beginning of the project, you are not sure and you don’t have any guarantees, 100% that you will find inefficiencies in the process, which will have bigger value than the* ***cost*** *of the project. So its a risk project where you can invest a lot of money but at the end didn’t find any important or significant problems, bottlenecks, yeah. So this is number one, it’s expensive.”*

“I think it’s a really good tool again I will say from my experience with Celonis I think it’s a pretty good tool but I think the ***cost*** *associated with it, that cost structure aspect of it and having that budget so that adoption thing is slow at*

*least. I think you need to have like dedicated resources as like **a lot of investment needs to be done** in training of the resources, getting the license fees setup and all of that. I think the cost associated with it and the cost could be worth like financial human capital cost and making sure that the investment is there so that people… right people…"*

When it comes to the challenges of implementing and using process mining, they can be grouped into technical and human challenges.

5.3.3.1 Technical Challenges

Data and Systems

The technical challenges point to process mining tools being sophisticated hence not easy to use and therefore require some level of expertise. Most respondents pointed to data as a big huddle as data in most organisations is either missing or not clean to be used. Given that data is the cornerstone of process mining, without it no mining can be done. Data is recorded in information systems and then mined to provide actionable insights for the organisation.

"So, the problem number three is IT systems if you want to make process mining project, you need to have an IT log. So, activity steps inside IT systems who record each transaction. And if you don't have this log inside the system, it's happening, sometimes people turn off recording of transactions and activity logs in databases and you won't see any, yeah, any transactions. Another problem that between if you want to have (end-to-end) process and they are executing in different IT systems, this IT systems can be not integrated between each other."

The difficulties that organisations face in accessing data sources that are located in various IT systems, the organisation's data quality due to inconsistent data collection practises, or the fact that the needed data is simply not available, are just a few of the problems with data that were discovered during the coding process. The necessity to guarantee the legitimacy and reliability of the data sources was mentioned by a few respondents, but it was not a common theme. The amount and quality of the data would also affect the process mining exercise's ability to produce high-quality insights..

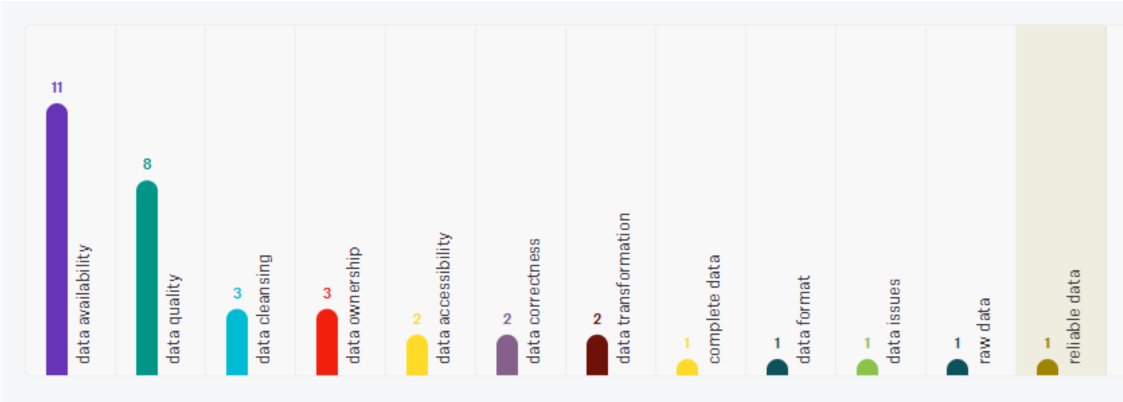


Figure 3: Key codes on data, source Researcher project on Atlas-ti

> *"And if your **data** is not rich enough, I mean let's say for example, you do a PO outside the system, only on the system you do a goods receipt, and then you capture an invoice. So not your full process is in the system. So it won't necessarily mean make sense for us to do a process mining, a full end to end process mining, because now we have to do it and scope out purchase order, then or something else is done on a different system."*

> *"It's basically a lot of thinking needs to be done on this preparation on data processing, something that is called ETL, Extraction Transformation Loading or whatever."*

> *"…the quality of **data** is not good and there is at least nobody there who can tell exactly what the meaning of the data is and how correct the data quality is. And that's one of the big challenge."*

5.3.3.2 Non-Technical Challenges

Change Management

The human challenges inferred to change management and mindset change where employees would be open to the level of transparency brought about by process mining. Moreover, just like any other technology change, adoption rates would differ in the organisation and convincing needs to be done to get buy in from the operators who use the organisations systems and well as the data owners to allow access to the necessary data in the organisation that can be mined into insights.

*“So and I think the biggest challenges are to involve the organisation to work with this **changed mindset**, with the insights from process mining, with a mission to improve, with a mission to change, and I think in my opinion I think that’s the biggest challenge”*

*“The shortcomings of it are that, when you introduce a new technology it’s a problem of **change management**. First, if you want people to trust the outcome of a tool like Celonis or whatever tool they’re using is that first you have to teach them what the technology does; you have to make them believe….”*

*“The problem is this tool actually gives you incomprehensive level of transparency, **with transparency comes resistance to change**.”*

5.3.4 Summary of the Findings of Research Question 1

The findings of research question one point to process mining being valuable to organisations that use it. The benefits and value of process mining include better decision making, cost savings and enhancement of business processes through automation. However, a number of building blocks are required so that organisations can realise the benefits of process mining. These include availability of information systems used to record data in the organisation, clean data in a format that can be used in process mining as well as experts that can support with mining and analysing of the data.

Moreover, given the investment cost of the tool, organisations can conduct pilot initiatives to investigate the best area to implement and to implement fast to ensure they get the ROI of the tool. Nonetheless, it was clear that organisations still need a lot of human intelligence and expert intelligence to actually get true value from process mining. The organisation needs to have dedicated resources and training needs to be done to ensure employees know how to use the tool. Nonetheless, the benefits seem to outweigh the challenges of process mining contributing to its growth and usage withing different industries.

5.4 Research Question 2:

How is value generated from the use of process mining?

The aim of the second research question was to understand the steps that should be taken by an organisation to gain value from process mining. Several key activities emerged as necessary to ensure successful implementation of process mining. These activities include planning, data extraction and processing, mining and analysis and finally improvement and monitoring. The process of generating value from process mining was highlighted as a key one given the inputs required and the talent.

Most respondents alluded to having the right data in the first place which required analysts to review organisations systems for congruence and completeness of data.

> *"It's basically a lot of thinking needs to be done on this preparation on data processing, something that is called ETL, Extraction Transformation Loading…"*

Secondly respondents pointed to having the business provide the right information for the right algorithms to be set up. The business questions would either emerge from the business struggling in certain areas and not being able to meet targets or from the review of data.

> *"…So what time between creating purchase request and creating purchase order? or what is the time from purchase order and the goods receipt? yeah when we receive the goods on our stocks and to use in our production process for example. So how fast we can deliver these goods to the business …, yes on how procurement department executes. And such questions we were discussing with business, with stakeholders, after that we understood what is our process scope, and what IT systems we need to interact with."*

> *"And then I will add as well on business side, clarity of the goal so if you don't know what you want to achieve then well you will probably not achieve much because it is like you will either have money you are not sure whether you want to buy a Ferrari, truck or maybe bicycle. You really need to know because the only time you can start is when you know."*

> *“In my opinion, you have the business, that has to consider all the analyses, and not the IT, that’s the most important part. So the IT is important for data collection but then the process is running by the business and the business is responsible for the process, and so then business can validate the data, and the results and so what’s for me very important for business is to consider of the analysed activities…”*

The ability of process mining to mine processes over and over again at no additional cost was highlighted as an advantage as the business can run the tool as many times as possible to draw further insights. This is what comes in handy especially with monitoring whether the process improvement actions that have been implemented are actually bearing the needed results.

The fact that the process mining tools come with dashboards to help in monitoring of set improvement KPIs was also highlighted as an advantage of this new tool. This means organisations do not need to have separate power BI tools for monitoring of KPIs. The completeness of the process mining tools was mentioned as a key advantage to traditional BI tools.

> *“With process mining and Celonis, which I guess most of other software they do that. So what it does is, you do your analysis, your analytics on the system, on the Celonis itself and then even your reporting because now it shows you a dashboard, you don't need to take your results to Power Bi. So you can do a dashboard already to the system itself and with one page you can show them to say this is what is happening and it gives you that capability of choosing or filtering and doing everything in one.”*

5.4.1 Summary of the Findings of Research Question 2

The findings from Research Question 2 seem to indicate a linear yet iterative process of getting insights from process mining. Coming up with the business questions or goal, data collection and mining, analysis then process improvement. All these steps are led by a project lead however it was clear that business needs to take ownership and ensure data quality and correctness as well as provide information based on the insights drawn from process mining. Finally, given the live data capability of process mining, organisations can look six months prior or after implementing process mining to monitor progress of improvement actions and validate whether the right decisions have been made.

5.5 Research Question 3:

What is the value of process mining in strategic-decision making in organisations?

The third question was meant to dig deeper into the value of process in driving strategic decision-making. So far literature had confirmed the value of process mining in driving operational and tactical decision-making however limited studies had tried to look at strategic decision-making. Respondents agreed with the value of process mining in driving operational and tactical decision making however there were conflicting views on whether process mining can actually drive strategic decision making.

> *"I would really see that especially at the moment how we are utilizing process mining in the company that the main focus on rather helping in finding opportunities for improvement at rather operational level not at strategic level. But as any BI solution I would imagine also that it could be applied to some strategic decisions, we are just not there yet"*

Moreover, the researcher had to explain what was meant by strategic decision-making as different respondents had different understands of the term strategic decision.

> *"So usually when people talk about strategy they think high level strategy but strategy affects even the smallest team also. So even if you have a three member team you have to have a strategy on how you're going to operate as a team for the entire year. So based on that the application of process mining will be very different."*

> *"It actually depends on strategic decisions selection, ERP system to be used that's in my opinion also a strategic decision but that's another kind of strategic decision to enter another market. So I don't know if you can use process mining to enter another market, that's …"*

“For your research also, decision is typically associated with a solution. Now decision happens in multiple levels, decision to know what to focus on, decision on how to focus, and decision to figure out which solution to implement. All of these are decision you’re making towards the solution and towards a particular outcome. That’s why I said it depends on what level and you make decision at every step of the way.”

What became clear is process mining supports in the execution of strategic decisions as one respondent rightfully said:

“It can support your strategy not develop. You need to develop your strategy but this can be a tool to help you achieve, execute your strategy or implement your strategy. So it’s more around implementation so you develop your digital strategy or digital roadmap etc. and process mining actually could be a part of your roadmap transformation.”

Some respondents agreed that process mining provides value when it comes to strategic decision-making. The respondents were able to provide concrete examples of the same.

“Yes of course it’s definitely beneficial from a strategic standpoint. I think this is more of an insight generator process mining that depends on what your strategic activities are, based on that you can sort of fine tune and get the insights that you need to help you with whatever your key strategic decisions.”

“And it was one of those so going back to like your main topic, your project aim about where can you utilize this for strategic decision? So in that case of returns processing we were also able to through process mining be able to pair location of the customers or geographic location of customers. And we are able to see okay, it takes so much when you compare different geographies. Sometimes it's towns that are really close to each other but depending on which return centre we are processing their returns, it would take much longer. So at a ***strategic*** *level we were able to make those changes to say, hey all these towns that are in this area should be directing all their returns to this return centre and if needed we need to increase capacity of this return centre or we need to build a new return centre. So you*

could make decisions like that based on the data because you can see that, based on the zip code of where the customers are sending our returns from, literally because sometimes you can have a situation where the zip code on this side of the street is one zip code and then across the street it's already another."

5.5.1 Summary of the Findings of Research Question 3

The findings from Research Question 3 seem to indicate that there is value of process mining in strategic decision-making. The findings indicated that in some instances the value of process mining in strategic decision-making was clear and the proper examples were provided.

5.6 Conclusion

This chapter presents the research results from the three research questions posed in chapter three. The findings suggest that process mining is valuable to organisations including in strategic decision-making. The most important conclusion derived from this study is that process mining is valuable to organisations since it allows for the identification of problems and provides specific improvement suggestions for business process.

All participants were aware of the benefits of process mining which include cost savings, objective decision making, enhancing business process transparency, compliance and enabling business process automation. Throughout the interviews, however, participants emphasised a desire for greater evidence that process mining adds value to strategic decision-making.

6 CHAPTER SIX: DISCUSSIONS OF RESULTS

6.1 Introduction

The findings from the preceding chapter's examination of data acquired from semi-structured interviews are examined in depth here. The discussion follows the order of the research questions posed and gives insights into the value of process mining in strategic decision-making. The findings are compared and contrasted with current research presented in chapter two in order to broaden the comprehension of the value of process mining in strategic decision-making. The study identified the benefits and challenges of process mining and how organisations can derive value from process mining for strategic decision-making. The sample criteria were process improvement professionals who have implemented process mining in their organisations. The participants' responses confirmed that process mining is valuable to organisations however the extent to which it can support strategic decision-making remains unknown.

6.1.1 Celonis: Process Mining Software

A general finding of the research pointed towards process mining software. Given that the objective of process mining is to identify and improve actual processes using data extracted from information systems (Rojas et al., 2017), there are several commercial and non-commercial process mining tools available. According to the findings, Celonis emerged as the most prevalent process mining software solution as it offers a straightforward visual representation and graphical user interface (Corallo et al., 2020). Furthermore, Geyer-Klingberg et al. (2018) state that Celonis has been used by thousands of people all over the world.

In their study on 'using process mining to help theorising about transformation in organisations,' Grisold et al. (2020b) utilised Celonis graphics to illustrate a visualisation of a Dutch company's purchase order handling process. Their research highlights that such a representation might serve as a beginning point for understanding how a normal job in the organisation is carried out (Grisold et al., 2020). Furthermore, Werner et al. (2020) in their research on 'embedding process mining into financial statement audits' include a model of a procurement procedure mined using Celonis. These examples prove the popularity of Celonis.

Additionally, by the end of 2019, Celonis which had 2.5 billion US dollars in net worth was given the coveted German Future Award by the German president (Grisold et al., 2021). The success of Celonis, which is a German start-up valued at $11.1 billion as of June 2021, demonstrates the practical use of process mining (Eggers et al., 2021). According to recent projections, the industry as a whole will rise tenfold over the next five years (Grisold et al., 2021), with a tripling to quadrupling of the present $160 million process mining market indicating its sustained relevance (Eggers et al., 2021).

Nonetheless, in their research experiment on 'process mining for six sigma, Kregel et al. (2021) chose to utilise ProM, an academic open source solution initially created by Professor van der Aalst and his team, instead of Celonis. The scholars selected ProM to avoid being restrained by licencing limitations or acquisition procedures, highlighting a drawback of choosing Celonis as the process mining software for any organisation over ProM (Dakic et al., 2018; Kregel et al., 2021). Interestingly, ProM was not mentioned by any interview participants in this study however it has been reviewed by other researchers and defined as a user friendly tool (Berti et al., 2019; Agostinelli et al., 2020)

Although this research found Celonis to be the most prominent tool, it is crucial to note that other tools, such as Signavio and MPM, were mentioned during the interviews. Since process mining was initially established as a scientific subject, the scientific community has made great contributions by building many additional software tools, algorithms, and approaches (Schuster et al., 2022). As a result, several modern process mining software tools have been developed and are constantly being enhanced (Dakic et al., 2018). According to van der Aalst (2018), there were over twenty five commercial process mining tools available in 2018, while Schuster et al. (2022) recently revealed that there are more than forty commercial process mining tools offered from different suppliers. Among the roughly twenty businesses that Gartner watches as vendors of process mining software are Celonis, Fluxicon, Signavio, Disco, Kofax, Apromore, and Software AG (vom Brocke et al., 2021; Kurganov et al., 2021; Martin et al., 2021; Leemans et al., 2019; Dakic et al., 2018; and Rojas et al., 2017).

6.2 Research Question 1

What is the value of process mining in organisations?

The first research question aimed to confirm what is present in current literature on the value of process mining. The interview questions sort to understand further the processes that use process mining as well as the benefits and challenges. The findings indicate a variety of processes that can be improved using process mining as well as benefits and challenges.

6.2.1 Processes that use Process Mining

The findings indicate three main processes that use process mining regardless of industry. These are procure to pay, order to cash, and logistics processes which are consistent with literature (Kurganov et al., 2021). In addition to analysing the industrial perspective, Zerbino et al. (2021) included a functional viewpoint based on Porter's value chain to their literature review on process mining. This functional viewpoint includes the value chain's eight functions: operations, logistics, marketing and sales, service, research and development (R&D), procurement, and infrastructure maintenance. Literature offeres examples of organisations employing process mining in all of these processes (Grisold et al., 2021; Faizan et al., 2021).

Evidently from the findings of this research, procurement is the main process that organisations use process mining for because procurement and supply chain operations are becoming increasingly transparent and traceable (Dakic et al., 2018; Thiede, et al., 2018). The initial step while using process mining in procurement is to discover problems, such as fraud and workarounds (Faizan et al., 2021). For example, a prominent European bank's procurement procedure was found to have internal control infractions. The second step is to analyse and enhance business processes. In this regard Zerbino et al. (2021) provide the example of how three manufacturing enterprises used process mining to improve and standardise their information system-supported procurement processes.

Moreover, according to Zerbino et al. (2021), logistical operations such as shipping and warehousing are ideal for process mining applications. This is due to the fact that they are distinguished by sequential, repeated, and traceable operations, and the event data which is created by information systems. Thus, process mining may efficiently address logistics process inefficiencies, deviations and bottlenecks (Kurganov et al., 2021; Faizan et al., 2021).

Finally, the majority of the studies look at essential business processes like purchase-to-pay or order-to-cash (Thiede et al., 2018; Eggers & Hein, 2020) which were found in this research. Grisold et al. (2020a) demonstrate the use of process mining in the purchase-to-pay process at Deutsche Telekom and Vodafone. Deutsche Telekom claims it reduced its cash discount loss by 20% and increased transparency and process uniformity across subsidiaries. On the other hand, Vodafone used process mining to promote uniformity in its purchase-to-pay process which resulted in more than a 10% increase in error-free transactions and a 20% reduction in market entry time (Grisold et al., 2021).

6.2.2 Benefits of Process Mining

The key themes that emerged on the benefits associated with process mining are enabling better decision-making, enhancing business process compliance, transparency and automation and finally enabling cost savings. This is in alignment across various literature sources which mention that organisations use process mining technologies to assist in business process improvement, automation, compliance and operations (Dakic et al., 2019; Eggers & Hein, 2020; vom Brocke et al., 2021; Zerbino et al., 2021).

6.2.2.1.Enabling Better Decision-Making

This study found that using process mining leads to better decision-making. The capability of process mining to find root causes of problems in the organisation ensures that once a decision is made it seeks to solve the real problem. This is in alignment with literature when Zerbino et al. (2021) mention that process mining provides management benefits such as improved decision-making. Various other scholars also point to the benefit of decision-making as a key value of process mining (Grisold et al., 2021; vom Brocke et al., 2021).

Furthermore, vom Brocke et al. (2021) emphasise that process mining uses data to make collaborative decisions. This is significant since judgments frequently rely on subjective interpretations while process mining has the potential to allow novel management techniques that rely on real-time data regarding process activity (Intezari & Gressel, 2017). This study found that data-driven decision-making is the core of process mining that supports decision-making in organisations (Faizan et al., 2021).

Lastly, not all process participants may adhere to ideal processes designed in the organisation. It is conceivable, for instance, that performers do not follow conventional operating procedures because they have discovered more effective means of carrying out the activity (Dakic et al., 2019). To comprehend why this is the case, all process participants must be able to articulate their reasoning and the surrounding contextual information (Grisold et al., 2021). This data may then be utilised to make better future decisions or to inform process redesign projects. For example, one may schedule meetings with numerous stakeholders to examine and debate the findings of process mining (Dakic et al., 2019). In summary, this study revealed that process mining has business value as an enabler of better decision-making.

6.2.2.2 Enhanced business process transparency

This study found transparency as a key and inevitable value of process mining. The capability of process mining to discover the actual process, show deviations and who does what and when came out as a clear value using the process mining tools. Eggers et al. (2021), agree that the majority of process mining research emphasises transparency of process flows as a critical value of process mining. Process mining facilitates the finding of processes executed in a given context and can provide insights into both common and exceptional process flows (Martin et al., 2021). The study found a definite propensity to monitor process performance and boost process efficiency based on process mining-induced transparency. This implies that adopting process mining necessitates dealing with enhanced organisational openness (Martin et al., 2021).

According to this study, process mining enhances openness; nevertheless, it must be compatible with organisational culture, or an organisation must guarantee that its cultural values are compatible with this technology so as to affect processes (Grisold et al., 2020). Furthermore, Grisold et al. (2020) examine the concept of embedded culture in this context, which suggests that management practises should include values that must be congruent with the organisation. The same might be stated about the application of process mining. Trust will be advantageous to the application of this technology requiring organisations to incorporate this values into daily operations (Grisold et al., 2020). This may need that organisations unlearn current procedures and prejudices. Therefore, more study is necessary to investigate the impact of cultural values on process mining implementation.

According to literature, greater openness may have both beneficial and bad consequences (Eggers et al., 2021). On the one hand, transparency has the potential to improve communication patterns and cooperation among employees (Dakic et al., 2019). On the other hand, if employees perceive they are being observed, it may generate mistrust and resistance. Understanding these dynamics might assist in the development of more prescriptive concepts about the use of process mining inside organisations (Grisold et al., 2020). Consequently, transparency extends to organisational structures, which manifest in staff roles and assignments, demanding an open organisational culture (Cummings et al., 2020).

Furthermore, according to a recent survey of 360 German companies, 81% have used process mining to analyse their process landscape (Eggers et al., 2021). For example, in the financial business, process mining is used to uncover the core causes of high cycle times in service processes, such that after identifying bottlenecks, alternative, quicker workflows may be presented, resulting in enhanced efficiency that can be calculated using simulation models (Eggers et al., 2021). This demonstrates how process mining is helping organisations gain transparency and improve their processes to accommodate quickly shifting business needs and customer expectations (Dakic et al., 2019).

Driving Compliance

The value of process mining in driving compliance in organisations came out strongly in this research. Currently the Sarbanes-Oxley Act (SOX) and the Basel II Accord put emphasis on corporate governance, risks, and compliance in organisations (Eggers & Hein, 2020). Process mining techniques enable more stringent compliance checks and the evaluation of the quality and dependability of data on an organisation's core processes (Dakic et al., 2019). Process mining techniques have advanced tremendously and as a consequence, process mining may now benefit management trends such as process optimisation and compliance (Eggers & Hein, 2020). Process mining helps auditors authenticate information about organisations by establishing whether they carry out business procedures within the rules and regulations established by management, governments, and other stakeholders (Werner et al., 2021).

Furthermore, process mining enables process managers to examine what actually takes place with organisational processes, such as undesired process patterns and compliance difficulties (Geyer-Klingberg et al., 2018). Conformance verification is recommended to determine how well existing procedures conform to internal and external standards (Kregel et al., 2021). Process mining is thought to be effective in verifying compliance with the new procedures and identifying any discrepancies (Geyer-Klingberg et al., 2018). Additionally, Grisold et al. (2020) report that process mining is used by over one hundred and fifty companies for auditing and compliance, halving the time required for client audit preparation. Furthermore, enhanced openness and automatic insights into audit risks and compliance violations increased customer satisfaction (Werner et al., 2021). In conclusion, process mining fundamentally facilitates process compliance.

6.2.2.3 Enable Cost Savings

This study found that process mining enables cost savings by improving work efficiency or the time spent performing certain tasks and activities. Process mining is linking with cost and expenditure reduction by finding processes that are outdated or that may be automated. This finding aligns with the core objective of process mining as a process management approach that assists users in quickly and objectively determining and optimising organisational processes by analysing business data and displaying real process flows (Leno et al., 2021). As a result, process mining has the potential to significantly cut the time and expense required to comprehend present procedures and additionally provide insights to optimise processes that lead to cost saving (Kregel et al., 2021).

Additionally, according to Grisold et al., (2021), process mining has had a variety of effects on hundreds of organisations worldwide, including cost savings and value innovation. Moreover, the fact that the same analysis may be done at any moment nearly without additional expenses, speaks to the cost effectiveness of using this tool (Graafmans et al., 2020). As a result, improvements based on ongoing evaluation of the consequences of modifications can be repeated at no additional costs. This sort of process mining expertise can assist in resolving issues that conventional BI tools cannot (Kregel et al., 2021).

Moreover Leno et al. (2020) states that on the basis of process mining estimates, organisations may develop recommender systems that recommend particular measures to save costs or decrease the flow time. Supporting this, Grisold et al. (2021) found an organisation that recognised possibilities and needs for robotic process automation after analysing the customer onboarding process resulting in the development of new business software and a 42% reduction in full-time equivalents (FTE). This ultimately led to increased process efficiency and reduced costs. In summary, process mining enables cost savings in the organisation by improving and optimising business processes.

6.2.2.4 Enhanced business process automation

Another key theme found in this research on the value of process mining is in regards to enhancing business process automation. Since processes are more transparent due to process mining implementation, repetitive work that can be automated becomes highly visible in the organisation. This finding is aligned with other literature by (Carillo, 2017; Geyer-Klingberg et al., 2018; Leno et al., 2021).

Robotic process automation (RPA) employs software robots to mimic human jobs (Leno et al., 2021). After the documentation of a process workflow, simple rules and business logic control are setup and a virtual robot duplicates and automates the actions done by people in the information system (Carillo, 2017). Multiple robots create a virtual workforce, allowing the automation of many knowledge-related and back-office tasks formerly performed by human labour (Carillo, 2017). The virtual robots are embedded in existing information systems and perform repetitive tasks, frequently across many systems (Leno et al., 2021). Process steps may be completed indefinitely and are instantaneously expandable since robots can readily manage volume increases (Geyer-Klingberg et al., 2018)

Consequently, process mining offers the foundation to identify levers for optimising processes through RPA (Carillo, 2017). Process mining can extract automatable processes from records of user interactions with information systems (Leno et al., 2021). Process mining attempts to identify automatable processes, identifying variants of each recognised process, standardising and streamlining the discovered variants (Leno et al., 2021). The resultant process must be developed in a platform-independent language capable of being compiled and run by an RPA tool (Leno et al., 2021).

Following a successful deployment, organisations can repeat the process to find additional processes for automation (Dakic et al., 2019). Furthermore, Gartner (2020) emphasises in their new market guide for process mining that this technology is a vital enabler for RPA programs, as visualising and understanding the process context, as well as finding and prioritising possibilities for task-level automation. As a result, process mining may provide direction to RPA activities and lead to the most appropriate processes for automation (Geyer-Klingberg et al., 2018).

Examples are provided in literature where Grisold et al. (2021), report on an organisation that utilised process mining to analyse the client onboarding process revealed possibilities and needs for RPA resulting in the creation of a new business process which reduced FTEs by 66%. Another example is provided by Corallo et al. (2020), in a case study that focuses on the operations of a Belgian insurance company. Errors in document categorization were identified as a key cause of process inefficiencies and it was recommended to implement optical character recognition technology, which would change the document classification process from manual to fully automated, resulting in a significant increase in process performance (Corallo et al., 2020).

Within an organisation, there are typically hundreds of processes with varying levels of automation (Leno et al., 2021). To make a good candidate for automation, processes should be scalable, repeatable, and standardised therefore, automation must be used with caution if an organisation has complicated and non-standardized procedures (Markus, 2017). Furthermore, the expense of maintaining and servicing the robots may surpass the savings gained (Leno et al., 2021). It is crucial to evaluate the maturity of business processes before beginning an RPA program to identify which processes are sufficiently standardised to benefit from RPA and which processes might first benefit from harmonisation and standardisation (Geyer-Klingberg et al., 2018): process mining supports the identification of such processes.

Process mining helps organisations to swiftly measure the maturity of business processes and identify those with the highest automation potential (Geyer-Klingberg et al., 2018). Manual people are identified as dialogue users in information systems, whereas robots are identified as system users (Leno et al., 2021). The automation rate for each activity included in the information system may be calculated as the ratio of cases where an activity was conducted by a system user divided by the total number of occurrences of the activity (Geyer-Klingberg et al., 2018). The automation rate is included as a performance indicator to the process explorer within the process mining application and may be seen with the number of cases underneath the activity names (Leno et al., 2021).

Prior to process mining, in-person or videotaped interviews, walkthroughs, and extensive observation of people doing their daily activities, were being used to discover suitable processes for RPA (Geyer-Klingberg et al., 2018). However, replicating these steps with multiple variations is often time-consuming and expensive; this is where the value of process mining comes in. Analysts can now use process mining to discover potential processes for automation and analyse the possible advantage, expenses associated with automating the identified processes (Leno et al., 2021).

In conclusion, the process mining tool detects not only the potential for automation, but also the business impact of automation by presenting changes in throughput time and other process performance parameters as automation rates increase (Geyer-Klingberg et al., 2018).

6.2.3 Challenges of Process Mining

Several challenges of process mining were found in this study and can be categorized into technical and non-technical challenges.

6.2.3.1 Technical Challenges

Data and Systems

The research findings suggest that challenges of process mining with regards to data are unavailability of data, issues with data quality, lack of ownership of the data and inaccessibility or limited data access. This study found that data is crucial in ensuring successful implementation of process mining. These findings are consistent with current literature from (Janssen et al., 2017; Gupta et al., 2018; Dakic et al., 2019; Grisold et al., 2021; and Martin et al., 2021).

The first issue highlighted by this research is the lack of data. This refers to the circumstance in which distinct types of necessary information are absent from the information system indicating a fault with the data entering procedure (Berti et al., 2019). The second issue is data quality which includes inaccurate, imprecise, and irrelevant data as the three key components (Gupta et al., 2018). Inaccurate data is a situation in which data may exist in an information system, but may have been incorrectly recorded based on context knowledge. In the case of imprecise data, the recorded entries are excessively coarse, resulting in a loss of precision. Such imprecise data hampers the execution of analysis requiring a more precise value and can lead to erroneous findings (Berti et al., 2019). Finally, irrelevant data refers to the situation in which the recorded data may be useless for analysis, necessitating another relevant data entry to be extracted from the data input by filtering or aggregation (Eggers & Hein, 2020). However, in a number of instances, such data translations are not simple, presenting a challenge for process mining implementation (Dakic et al., 2019).

During data collection and integration for process mining, the data owner may be ambiguous. Moreover, once data ownership is established, it must be indicated if and how the data may be utilised (Grisold et al., 2021). Existing ownership structures must be modified to fit the needs of big data, according to arguments by Carillo (2017). Moreover, data accessibility relates to disparities in authorisation to access and utilise essential data. Teams entrusted with data integration apparently have difficulty getting the data making it difficult to implement process mining (Dakic et al., 2019).

This study revealed a number of data quality concerns which hinder the applicability of process mining and lower the quality of the extracted insight. In conclusion, gathering data for process mining necessitates awareness and management of these data problems (Carillo, 2017). There is an urgent need for process mining research to include focus on methods to address these data problems. Organisations need to create data collection strategies, beginning with a study of the insights required and the analytic potential of available data (Grisold et al., 2020).

6.2.3.2 Non-Technical Challenges

This research found two main non-technical challenges, which include understanding process mining output and change management (Martin et al., 2021). Different levels of analytical and decision-making competence influence how process mining insights are extracted and implemented by users. Since its inception more than a decade ago, process mining has made substantial progress. Numerous successes and the great potential of process mining have fuelled interest in the field. Despite this success and the range of process mining approaches and tools, it is still difficult to extract the necessary insights from data (Dakic et al., 2019). Particularly, business users and technical specialists need to collaborate to draw the necessary insights from process mining (Faizan et al., 2021). The business experts and process analysts, who should work together to evaluate the analytical findings and guarantee that they are relevant and useable (van Eck et al., 2015)

In addition, this study indicated that mistrust may exist due to the fact that many actors' behaviours are recorded and individuals feel as though they are being observed (Eggers et al., 2021). Consequently, process mining may affect the culture and working environment of the organisation. These changes in addition to adoption of a new technology in the organisation can lead to resistance to change (Sun, 2018; Grisold, 2021).

6.2.4 Summary Discussions of Research Question 1

The first research question sought to confirm the findings of the most recent academic studies on the value of process mining. The interview questions were developed to help better understand the processes that use process mining as well as the benefits and challenges. The results highlight a number of processes that can be enhanced via process mining, along with advantages and difficulties.

Process mining is used in procurement, order-to-cash and logistical processes and provides management benefits such as improved decision making and cost savings (Martin et al., 2021). The majority of research emphasises the transparency of processes as a crucial value of process mining with the additional value of facilitating compliance by discovering areas for improvement by continuously monitoring end-to-end business processes (Geyer-Klingberg et al., 2018).

Process mining can extract automatable processes from information systems and organisations can use these data to discover processes for automation and analyse the possible advantages and costs (Geyer-Klingberg et al., 2018). Processes should be scalable, repeatable, and standardised to be automated. Therefore, it is critical to assess the maturity of business processes prior and automation must be used with caution if an organisation has complicated and non-standardised processes (Leno et al., 2021).

Several challenges of process mining were mentioned and can be grouped into technical and non-technical challenges. Since its start over a decade ago, process mining has achieved substantial development. Despite this, real-world implementations of process mining are typically challenging, because of data and change management issues (Carillo, 2017). Ultimately, process mining must take into account the users of the technology and should also consider the challenges and how they can be mitigated (Grisold et al., 2020).

6.3 Research Question 2

How is value generated from the use of process mining?

The aim of research question two was to interrogate how the benefits established from research question one are arrived at using process mining and how the challenges can be mitigated through the steps that organisations take to implement process mining. The results of research question two confirm that there are certain steps that organisations must take in order to get value from process mining. Planning, data extraction and processing, mining and analysis, and process improvement are all part of the implementation process to get value from process mining.

Graafmans et al. (2020) provide the closest advancement to a process mining methodology to date. Van der Aalst (2011) offered the first and most significant addition to process mining methodology by presenting the lifecycle of a project implementation, while De Weerdt et al. (2013) supplied phases to be followed. Later, van Eck et al. (2015) updated the phases with some degree of depth for activities such as data extraction based on the information system and outlined the precise procedures to be taken, which are explained further below:

6.3.1 Planning

This study found that clarity in the business goals and objectives to be supported by process mining is the first thing that organisations should do. This coincides with the planning stage of process mining appearing in literature (Graafmans et al., 2020). The planning stage's goal is to establish the project and the objectives of implementing process mining (Ramires & Sampaio, 2022). Before beginning process mining initiatives, the key aims should be established and considered. This phase creates objective-related business questions (Graafmans et al., 2020). The abstract business questions from this phase are then clarified through exploratory analysis, yielding business questions (van Eck et al., 2015).

The preliminary data preparation is performed to assist in identifying appropriate business objectives and to accompany business questions relative to one or more aspect of business processes, such as time, quality and resources (Graafmans et al., 2020). This needs to be established so that during exploratory mining and analysis, a quick summary of the process may be drawn from the data (van Eck et al., 2015).

The objective of this phase is to gain an understanding of the business process and its primary challenges. Not only are the improvement targets to be achieved by implementing process mining set, but also the questions to be answered by using process mining are formed (van Eck et al., 2015). Additional, setting a reasonable time range for process mining is done at this stage and necessitates either expert judgement or an iterative analytical technique (De Weerdt et al., 2013). In general, creating an appropriate scope may be accomplished by carefully reviewing the various actions recorded in the information systems. Additionally, data frequently provides helpful information on how to recognise various business activities within an information system to better define scope during the design phase (Graafmans et al., 2020). The output of this stage, the well-established business questions are used as input for the next stage of data extraction and processing.

6.3.2 Data Extraction and processing

The findings of this study show that data is critical for process mining implementation. Moreover the data needs to be available and in a format that can be used for process mining. The information systems that enable the analysis of the execution of the indicated business processes are the stage's inputs, together with the research questions (Graafmans et al., 2020). The primary goal of this stage is to generate data and to handle the data in such a manner that they are best for the next stage of mining and analysis (Aguirre et al., 2017). Additionally, the preliminary data preparation offers information which can help the planning step to identify further business challenges that may have been missed and strengthen business case for the process mining implementation (Graafmans et al., 2020).

In this stage, data is aggregated, enriched, and filtered (van Eck et al., 2015). Additional data from the organisation's information systems is collected and processed to produce clear, filtered, enriched and validated data that can be utilised as input to the next stage of mining and analysis (Graafmans et al., 2020). This phase seeks to identify the necessary data for the research, extract it from the information system, and assure its quality for further analysis utilising process mining techniques (Aguirre et al., 2017). This process is overseen by the data analyst in the organisation (Graafmans et al., 2020) however, the most crucial responsibilities are those of business experts and process analysts, who work together to evaluate the data and guarantee that they are relevant and useable (van Eck et al., 2015).

Additionally, the data exploration process begins in this stage, when a large amount of statistical data is evaluated (Aguirre et al., 2017). A number of preliminary visualisations of the process may also be obtained at this stage (Graafmans et al., 2020). Business experts can ensure that the input data is suitable for further analysis by iteratively modifying the process scope and time frame depending on these exploratory phases. It is critical to have a feedback loop for adjusting the process scope and time period (De Weerdt et al., 2013).

6.3.3 Mining and Analysis

This stage involves four activities: process discovery, compliance verification, enhancement, and process analytics (Graafmans et al., 2020). Conformance checking techniques may be used to check the conformity of relating business operations to variables such as time, quality and resources (Aguirre et al., 2017). Using data mining techniques or visual analytics, the outcomes may also be employed to enhance process models with additional aspects (Werner et al., 2021). The output from the analysis step provides results that address organisational performance goals and objectives.

During this stage, the data is examined more closely, the team, coordinated by the process analyst, conducts thorough data analysis in order to identify possible causes for the difficulties found in the planning phase and improvement alternatives that can be implemented in the next step (Aguirre et al., 2017). As a result, the examination at this level is more in-depth and rigorous. The primary input comprises of data generated in the preceding phase and business issues from the first phase (Graafmans et al., 2020). With this information, process mining is used to find the real process, evaluate its performance and interactions among its participants, and assure adherence to the associated business rules and procedures (Aguirre et al., 2017).

6.3.4 Monitoring and Improvement

The goal of the process monitoring and improvement stage is to enhance the actual process based on the insights gathered and ensure consistency of improvement based on the objectives set during stage one (Aguirre et al., 2017). Inputs are the process model, performance, and compliance outcomes from the analysis stage (Graafmans et al., 2020). This stage's outcome is process changes that address the insights revealed in the previous stage. The analysis' findings are a great place to start for efforts aimed at streamlining or reengineering the current business process (Graafmans et al., 2020).

Furthermore, process mining may be used to determine the expected impact of various improvement measures and to pick those with the greatest impact if applied (Aguirre et al., 2017). As the business side is where the process improvement activity is actually carried out, the business user is in charge of implementing and managing the required process adjustments using the identified improvement opportunities as input (Graafmans et al., 2020). In addition, because business expertise is necessary at this stage and assessment happens on the business side, it is the responsibility of the business user to evaluate if the process enhancements generated the anticipated benefits (Graafmans et al., 2020). This stage's deliverable is further enhancements toward business goals (Aguirre et al., 2017).

This phase consists of two parts: monitoring and assessment. During monitoring, process execution is observed in respect to performance metrics. During assessment the organisation analyses if the effect of the adjustments matches the desired outcomes and if the process has been successfully improved (Graafmans et al., 2020). Monitoring may lead to new outcomes, which could provide new business difficulties and need repeating the steps (Aguirre et al., 2017).

This stage ultimately connects the findings of the analysis seeking recommendations for enhancements that may assist the project in achieving its aims by diagnosing, verifying, and validating improvement actions (van Eck et al., 2015). One of the disadvantages of process mining is that process analysts are often not business experts for the researched process, because of this, they struggle to pinpoint the causes of unexpected analytical results. As a result, process specialists must be included in the verification and validation of the outcomes (van Eck et al., 2015).

6.3.5 Summary Discussions of Research Question 2

The purpose of research question two was to examine how process mining is used to achieve the benefits identified in research question one and how the problems can be lessened by the actions that organisations take to adopt process mining. The steps identified include: planning, data extraction and processing, mining and analysis, and process improvement recently presented by Graafmans et al. (2020). In the first step of a process mining business objectives and scop of project are defined. These inform the second stage of data collection and processing where data is accesses from information systems and processed to be valuable for process mining. In the third stage of data mining and analysis phase, analysis is done that provides insights that are used in the final stage of improvement and monitoring (Graafmans et al., 2020). This methodological approach has been refined over time and can serve as a guideline for organisations while implementing process mining to ensure they realise the benefits and mitigate the challenges.

6.4 Research Question 3

What is the value of process mining in driving strategic decision-making in organisations ?

The purpose of the third research question was to go more deeply into how process can influence strategic decision-making. Process mining has been shown to be effective in guiding operational and tactical decision-making thus far, but few studies have attempted to examine strategic decision-making (Zerbino et al., 2021). The findings of this study provide evidence of process mining supporting strategic decision-making in organisations.

The value of the process, specifically when it comes to strategic decision-making, is not straightforward. So far literature had confirmed the value of process mining in driving operational and tactical decision-making however limited studies had tried to look at strategic decision-making (Grisold et al., 2021). This research resolved to highlight the value of process mining in strategic decision-making and provided some real-time examples.

Martin et al. (2021) state that the data-driven nature of process mining insights facilitates evidence-based process optimisation and strategic decision-making. And as such, data requirements should be stated in relation to strategic objectives. This research found that process mining should align with the strategy of the organisation which is in line with Grisold et al. (2021). In order to guarantee an adequate alignment of the process mining project with the organisation's strategy, a gap analysis must be conducted so that the expected performance of key management indicators of the process can be used as an evaluation reference (Yeow et al., 2018). This is central to the definition of the objectives and questions to be solved with the process mining project during the planning stage (Aguirre et al., 2017).

According to research, using AI can result in more effective strategic decision-making and implementation (Duan et al., 2019). There are fears that the amount of data may become unsustainable, necessitating the usage of computer technologies to assist organisations in making decisions (Leyer & Schneider, 2021). The availability and potential of Big Data is revitalising AI as technologies quickly improve. The current generation of AI technology has increased its ability to make data-driven forecasts while lowering forecasting costs (Jarrahi, 2018). As an AI enabled technique, process mining should also aid in strategic decision-making. However, the vast majority of AI's advantages are anticipated to materialise in the long term and hence organisations should not expect to reap benefits in the short term (Jarrahi, 2018). This explains why the findings of this study may be inconclusive advocating for a longitudinal study that can analyse organisation performance over a long period of time to uncover further insights.

The capacity of an organisation to make timely and high-quality decisions determines its performance (Alhawamdeh & Alsmairat, 2019). Using dynamic capabilities to adapt to quickly changing business environment ensures that organisations gain a competitive edge (Haarhaus & Liening, 2020). Strategic-decision making is a dynamic capability and supported by process mining it can make an organisation competitive.

Ransbotham et al. (2018) argue for the integration of dynamic capabilities theory with strategic foresight research. Connecting these study streams might lead to fresh insights into how businesses can flourish in hypercompetitive conditions. Organisations must observe market behaviour in order to gather knowledge and strategic positioning possibilities (Mikalef & Pateli, 2017). Through process mining, decision makers may quickly scan the environment and get critical information. Process mining finds dysfunctionality that contributes to strategic blind spots and reveals realised business processes (Grisold et al., 2021).

6.4.1 Summary Discussions of Research Question 3

The value of process mining in operational and tactical decision-making is well established. The availability and potential of Big Data is revitalising AI as technologies quickly improve. There are fears that the amount of data may become unsustainable, necessitating the use of AI (Leyer & Schneider, 2021). Process mining is a technique that employs AI to aid in strategic decision-making. Using dynamic capabilities to adapt to quickly changing business environment ensures organisations gain a competitive edge (Duan et al., 2019; Haarhaus & Liening, 2020). The vast majority of AI's advantages are anticipated to materialise in the long term.

6.5 Conclusion

The study identified the benefits and challenges of process mining and how organisations can derive value from process mining. Celonis emerged as the most prevalent process mining software solution because it offers a straightforward visual representation and graphical user interface (Grisold et al., 2021). The findings indicate a variety of processes that can be improved using process mining. The majority of studies look at essential business processes like purchase-to-pay or order to cash (Eggers & Hein, 2020). Gathering data for process mining necessitates awareness and management of data problems. Existing comprehensive taxonomies may be utilised to identify data quality issues (Carillo, 2017).

Process mining has the potential to allow novel management techniques that rely on real-time data regarding process activity. Process mining enables the discovery of process execution in a given environment and can offer insights into unusual or abnormal flows. This study found business value in process mining as an enabler of better decision-making, transparency, cost saving and compliance. Process mining may be used to determine the expected impact of various improvement measures and to pick those with the greatest impact. This is put into practise by relating the analysis' findings to proposals for project improvement that would help the organisation achieve its goals.

Process mining's significance in operational and tactical decision-making is generally acknowledged. As technological progress quickens, Big Data's availability and potential give AI a new lease on life (Ransbotham et al., 2018). There are worries that the amount of data may become unmanageable and require the use of artificial intelligence (Leyer & Schneider, 2021). Process mining is a method that businesses can utilise with AI assistance. Businesses can gain a competitive edge by utilising dynamic capabilities to respond to a quickly shifting business environment (Haarhaus & Liening, 2020).

7 CHAPTER SEVEN: CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This study examined the value of process mining for strategic decision-making. Process mining literature was consulted, and interviews with seasoned process improvement professionals were conducted. The data obtained was analysed to identify themes and interpretations that align with the research questions. Dynamic capabilities theory informed outlook in exploring eclectic business contexts.

Literature posits that when organisations employ process mining as a dynamic capability to analyse and improve business processes, competitive advantages are secured (Faizan et al., 2021). Although some organisations are leveraging process mining, there have been few studies on usefulness to strategy, particularly from a business application standpoint. As a result, this study investigated how process mining could be utilised as a dynamic capability to support strategic decision-making for competitive advantage (Leno et al., 2021). Key findings are described in this chapter, along with implications for both academics and business. The chapter ends by outlining the limitations of the research and offering potential areas for further investigation

7.2 Principal Findings

As a main finding, the study exposed diverse benefits in process mining for strategic decision-making. Organisations stand to capture sustainable growth enhancements from adopting process mining. However, few real-life examples on the value of process mining in strategic decision-making were discovered through this research. Human experience and intelligence remain essential for the successful implementation of process mining as a dynamic capability (Eggers & Hein 2020). In tandem, data emerged an essential ingredient; its availability, accessibility and quality impact ability to extract and quality of insights. Additionally, Celonis, a process mining software stood out as the most widely utilised option.

The main processes being reviewed in organisations include procurement to pay, order to cash, accounts payable, accounts receivable and invoicing (Kurganov et al., 2021). These activities were highlighted as common across industries indicating flexibility of application within and across different organisations. Examples of usage of process mining ranges from the financial sector to e-commerce to transportation and logistics, demonstrating impact relevance in different sectors characterised by these processes.

The key benefits of process mining that emerged were: enabling better decision-making, enhancing business process transparency, business process automation, cost savings and compliance (vom Brocke et al., 2021). Nonetheless, there are challenges that come with implementing process mining, significantly: data quality and change management. The findings underscored access to appropriate data as critical foundation (Intezari & Gressel, 2017). This requires input from analysts to assess organisational systems for data congruence and completeness. Given the inputs and expertise required, business questions arise as data reveals granular details on underperforming assets or processes.

In brief, there is agreement on the value of process mining in supporting operational and tactical decision-making. However, respondents were not aligned in endorsing value of process mining for strategic decision-making. Evidence shows that while process mining does not lead to the formulation of strategic decisions, it does help during the development and implementation of strategy. More research is therefore required in this area.

7.3 Implications

7.3.1 Implications for Academics

The study's findings can be used to develop a process mining research agenda. The importance of process mining in strategic decision-making might help to identify high-priority research topics. The significant presence of nontechnical benefits suggests that process mining research has great organisational opportunities (Zerbino et al., 2021). This includes identifying the organisational characteristics that support this capability; and defining how related activities might be structurally entrenched in organisations with right team composition and capacities to realise benefits.

Moreover, related subjects within the process mining discipline are largely under-explored research areas, offering a rich foundation for future scholarly investigations (Grisold et al., 2021). For non-technical challenges such as change management, that is not specific to process mining, the extensive body of literature on technology adoption provides helpful inspiration (Sun et al, 2018). Researchers must carefully assess whether current information on technology adoption is applicable to process mining, or whether process mining adoption and usage necessitate the use of distinct approaches (Martin et al., 2021).

Simultaneously, the findings show that technical research should not be overlooked because it is a critical component in continuously pushing the frontiers of process mining (Graafmans et al., 2020). Particular attention should be paid to difficulties that cover research targeted at aiding with data preparation, addressing quality issues, and increasing the comprehension of process mining insights (Faizan et al., 2021). Significant research opportunities remain from both an input and output perspective for process mining; this is set to deepen insight into scope for deliverables.

Finally, the variety of outcomes, as well as the perception misalignment among practitioners on value for strategy, suggests that process mining research should explore emerging topics in related and relatable fields of study (Martin et al., 2021). Given growing reliance on big data, scholars posit that the value of process mining is expected to expand (Corallo et al, 2020). However, disparities in outlook for strategic relevance, necessitate research driven response.

7.3.2 Implications for Business

The study confirmed that data is the foundation of process mining. Organisations must treat data as critical input rather than a by-product. It is essential to collect clean, high-quality data that can be mined for greater insights. Lessons emanating from the domain of data warehousing are applicable to assure high-quality administration. For example, simple input checks can considerably minimise inaccuracies in records (Faizan et al., 2021). Furthermore, findings underscore the importance of ensuring that data is correct, complete and validated. Organisations frequently use multiple information systems; therefore, data correspondence across systems should be evaluated. Scholars caution that process mining can be harmful if applied on erroneous data (Martin et al., 2021). Therefore, organisations should take steps to reduce hurdles hindering data availability and access, whilst improving quality; a recurring problem for process mining implementation in organisations.

Process mining insights are not always helpful. The user may have difficulty comprehending the results or may be swayed to inaccurate judgments. In order to minimise such problems, the results should be presented in standardised format that is intelligible to end users. Furthermore, the reliability of the outcomes should always be explicitly emphasised. Examples include insufficient evidence to support specific conclusions, or data that produces patterns where none exist (Agguire et al., 2017).

A third consideration pertains to the benefits and challenges that may assist organisations in designing a process mining implementation plan. Initially, the clarity on benefits and challenges aides in prioritising advantages while also elevating concerns that may restrict the efficacy or efficiency of process mining (Martin et al., 2021). Later on, the outcomes and experiences can serve to assure quality control so that applicable benefits are realised and challenges addressed (Leno et al., 2021). This can be effective and attract management buy-in, through improving the process mining business case and further by integrating process mining activities with the organisation's strategic objectives, and making value obvious.

Explicit inclusion of process mining in the organisation's data governance policy and standards is set to encourage uptake. Initiatives to improve data registration must work in tandem with enhanced process mining training and development (Leno et al., 2021). Employees are more likely to support efforts aimed at improving data registration when aware of the advantages of process mining as well as the influence on work habits and outputs.

Providing a conducive framework is vital for success with process mining initiatives. The findings indicate need for organisations to invest in tool-based training, promoting data and process knowledge. This may be operationalised in various ways. For example, hosting inter-departmental workshops to identify dependencies across units operating on the same processes can help expose how activities might be better aligned (Martin et al., 2021).

Finally, the visibility afforded by process mining has organisational ramifications. It is critical to anticipate and address the enhanced openness brought about by process mining. Transparency may breed suspicion and a sense of being watched. As a result, cultural impact is regarded a vital component to harmonise interaction across teams (Grisold et al., 2021). A supportive organisational culture that incorporates principles such as trust and openness is required to enable effective process mining competency utilisation (Hollister et al., 2021).

7.4 Limitations

This study had various limitations in methodological and theoretical framing. First, the sample size was limited to 11 individuals, with one in South Africa, two in the United Arab Emirates, and eight in Germany. Despite significant efforts to broaden the study's reach and diversify respondents, professionals working in Germany made up the majority of the sample. This points to a lag in the level of maturity of process mining in other countries outside of Germany, where it originated. As a result of the low number of participants in various geographies, scope for thematic analysis pursuing international or regional distinctions was restricted (Flick, 2018).

Second, because the function of process mining in strategic decision-making is not well established in literature, the construct of process mining in strategic decision-making could not be fully characterised (Zerbino et al, 2021). In future, more detailed conceptualization of process mining for strategic decision-making might lead to better understanding of this construct.

Third, owing to time restrictions, this study was cross-sectional with interviews conducted once (Asiamah et al., 2017). Appointment cancellations and Europe vacation schedule tensions prevented capture of more participants who may have expanded insights. Furthermore, the researcher was unable to contact respondents for clarification or confirmation on the interpretation of the data gathered and analysed.

A fourth limitation pertained to cultural and linguistic differences. The bulk of the interviews were conducted in English, which for some participants, was not the first language of communication. Consequently, variations in interpretation of meaning and subtleties may have resulted in data losses during collection and interpretation processes (Brown & Danaher, 2019). Respondents' native countries included India, Bulgaria, Germany, and South Africa, all of which do not speak English as a first language.

Fifth, as characteristic of qualitative study, the findings are dependent on the opinions of a select group of specialists. The study was exploratory in nature; the sample size limited and hence statistical significance cannot be argued. Bias in responses cannot be explicitly removed (Gray et al., 2020). Therefore, the researcher could not form any assertions about the representativeness of the findings (Asiamah et al., 2017). Duplicating the study may result in dilution of any prejudice in responses.

Finally, the researcher was a novice in the field of academic research. This inexperience, may have coloured judgements in execution and interpretation of the research. Furthermore, one of the key challenges of qualitative work is the researcher's prejudices and preconceptions, which may alter results (Gaus, 2017).

7.5 Recommendations for future research

Process mining is attracting research attention. Tools for effective analysis and business process improvements are emerging. Replicating this study with experts from various geographical places other than Germany would strengthen generalizability of findings (Flick, 2018). Purposeful selection of specialists from diverse nations or areas is set to expose geographical and industry variations (Asiamah et al., 2017). Second, data from experts who have used process mining tools other than Celonis, would offer insight into alternative tools on the market and how these compare.

Future research should investigate the specific relevance or interpretation of value from process mining in strategic decision-making in greater depth. Furthermore, variation in evaluation, either by conducting in-depth conversations with experts or conducting case studies on the value of process mining in strategic decision-making may explain disparities observed in the respondents viewpoints (Zerbino et al., 2021).

Further studies are required to comprehend the interaction between various benefits and challenges (Dakic et al., 2019). Due to its exploratory nature, the current study did not investigate such relationships. Examining the link between phenomena might reveal that some benefits and magnify specific challenges, necessitating coordinated action. Furthermore rating the benefits and challenges can be useful to organisations to understand where to put their focus while implementing process mining (Faizan et al., 2021).

Furthermore, dirty data must be cleansed. Existing comprehensive taxonomies may be utilised to identify data quality issues (Dakic et al., 2019). Despite the fact that each of these taxonomies produces and subdivides the data issues in a different way, their findings are quite similar, showing the importance of this data quality issue. Although a lot of the obstacles in the preceding taxonomies are comparable to process mining data quality issues (Aguirre et al., 2017), the taxonomies are not exclusive to the process mining domain, which stimulates the creation of specialised research on this topic.

As a fourth consideration, the research findings could be utilised to develop process mining maturity models and related project portfolio management methodologies (vom Brocke et al. 2021). A organisation's ability to capitalise on opportunities while managing risks reflects its maturity. Following the identification of maturity levels, guidance for organisations to become more mature process mining users may be developed (Martin et al., 2021).

Finally, while research has focused on the good results of process mining, impact on strategic decision-making remains unclear (Zerbino et al., 2021). Future studies might look at how organisations function after applying process mining as strategic decisions are long-term. This may be further analysed and contrasted across time. Such findings might also result in the development of scenario cases over a period of time (Caruana et al., 2015). Future study may place greater emphasis on including comprehensive details of how organisations implemented process mining initiatives over time (Grisold et al., 2021).

7.6 Concluding statement

A significant finding from this study is that process mining application in organisations is valuable in the context of strategic decision-making. Process mining enables problem identification and provides precise recommendations for how to enhance business process. Process mining is becoming more popular, which is supported by the exponential growth in the amount of data stored in information systems and the need to sustain and extend competitive advantage in light of the volatile business environment (Corallo et al., 2020). This technology can help companies across industries achieve their objectives of creating new or improved products and services, lowering costs, and increasing productivity through automated and optimised operations.

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APPENDICES

APPENDIX 1: Interview Guide

Interview Schedule (Saunders & Lewis, 2018 p. 161)

Title: The value of process mining in strategic decision-making

Introduction:

- Thank the interviewee for attending the interview
- Outline the purpose of research and the interview
- Indicate to the interviewee that the interview is voluntary and they can stop at any time
- Inform the interviewee that the interview is anonymous and the data confidentiality will be maintained
- Confirm with the interviewee if okay to proceed with the interview
- If they are happy to proceed, ask them to read the consent form and to sign it; if not thank them for their time and close the interview

The interview questions:

General Clarifications:

1. Please state your title, position or role.
2. Please confirm the number of years you have used process mining.

Research question one: What is the value of process mining?

1. What has been the experience for you using process mining?
2. What are the main processes for which you have used process mining?
3. What benefits have you experienced from using process mining?
4. What are the downsides you have experienced from using process mining?

Research question two: How can process managers generate value from process mining?

5. How do you define the business questions that you would like to be answered by process mining insights?
6. How often do you generate insights from process mining?
7. How do you monitor the improvements derived from process mining?

Research question three: What is the value of process mining in strategic-decision making?

8. How do you analyse insights from process mining?

9. How do you embed the insights derived from process mining in long-term decision-making?
10. What challenges have you experienced in using insights from process mining to make long-term decisions?

APPENDIX 2: Copy of Consent Form

Informed consent letter

I am currently a student at the University of Pretoria's Gordon Institute of Business Science and completing my research in partial fulfilment of an MBA.

I am conducting research on Process Mining and am trying to find out more about the value of process mining in strategic decision-making. The interview is expected to last about an hour and will help me understand how process mining can be used in making strategic decisions. **Your participation is voluntary, and you can withdraw at any time without penalty**. All data will be reported without identifiers. If you have any concerns, please contact my supervisor or me. Our details are provided below.

Researcher name: Tabiness Simwa
Email: 21819867@mygibs.co.za

Research Supervisor Name: Rishal Balkissoon
Email: Rishal.Balkissoon@gmail.com

Signature of participant: ________________________________
Date: ________________

Signature of researcher: ___
Date: 10th August 2022

APPENDIX 3: Code list

name	comment	codegroup 1
accounts payable		Processes
accounts receivables		Processes
activity		
adoption		
audit to cash cycle		Processes
Automation	Merged from automate and automation	Process Optimisation
Best Practice Adoption	Merged from best practice and Best Practice Adoption	Process Optimisation
bot		Process Optimisation
budget		High financial cost of investment
business intelligence		
business process		
case		
Celonis		
change management		Change Management
comparison		
complete data		
compliance		
conformance		
cost		High financial cost of investment
cost of setting up		High financial cost of investment
cultural management		Change Management
data		
data accessibility		
data analysis		
data analysts		
data attributes		
data availability		
data cleansing		
data collection		

data correctness		
data engineers		
data entry		
data extraction		
data format		
data integration		
data issues		
data management		
data ownership		
data points		
data processing		
data quality		Data
data quantity		
data science		
data scientists		
data simplicity		
data transformation		
data validation		
database		
decision		
deviations		
ERP		
Europe		
European		
European clients		
European counterparts colleagues		
event		
expensive		High financial cost of investment
financial data		
financial human capital cost		High financial cost of investment
find bottlenecks		
full data set		
german		
human capital		
ideal process		

insights		
internal audit department		Processes
investment		High financial cost of investment
IT systems		
knowledge gap		
leadership		
operations strategy		
optimization		
order to cash		Processes
outdated data		
ownership		
plan to manufacture		Processes
process		
process identification for automation		
process mining		
Procure to Pay	Merged from procure to pay and Procure to pay processes	Processes
procurement		Processes
production		
purchase to pay		Processes
purchasing		Processes
raw data		
reliable data		
removal of bottle necks		Process Optimisation
repeated activities		
repetitive		
resources		
responsibility of the implementation		
rework		
rich data		
robotic process automation		Process Optimisation
root cause analysis		
SAP		
Signavio		

strategy		
strategy impementation		
systems		
technology adoption		
training		
transparency		
value in strategy		
visibility		