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Digital Transformation of Business Processes:

Exploring the Organizational Use of Business Process Technology and Its Implications on Business Process Management

Julia Angelika Hein, Master of Science

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1. Prof. Dr. Helmut Krcmar
2. Prof. Dr. Luise Pufahl
3. Prof. Dr. Michael Dowling

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Preface

As a kid, I always wished to be a writer one day. Little did I know, however, where my path would take me and what kind of book I would write. Now, as I am finishing my dissertation (which turned out much like a book, at least lengthwise—I am still working on myself to keep it short!), I could not be more grateful for where life took me. The last years have been an incredible journey, and I have learned and grown so much as a scientist, a colleague, and a person. Above all, however, this journey would not have been possible without the unwavering support and guidance of many people.

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Munich, 09.06.2023 Julia Hein (geb. Eggers)

Abstract

Problem Statement: In the era of digital transformation, organizations face the challenge of managing business processes in an increasingly dynamic and complex environment. Driven by these changes, traditional assumptions about business process management (BPM) and the role of information systems (IS) are challenged, raising the question of how BPM unfolds under the new paradigm of digital transformation. To this end, novel business process technologies have emerged to support BPM, offering organizations unprecedented business process transparency and automation capabilities. Diagnostic technologies like process mining enable the analysis of heterogeneous process data while automating technologies like robotic process automation (RPA) and distributed ledger technology (DLT) provide efficient and scalable automation options. However, organizations still struggle to leverage these technologies. In particular, organizations need to understand the antecedents necessary to adopt these technologies, how these technologies enable new approaches to BPM, and how, as a result, organizations can transform their business processes.

Research Design: To address these gaps, this dissertation builds on a constructivist research paradigm leveraging qualitative research methods to unravel the organizational use and implications of novel diagnostic and automating business process technology. First, taking the examples of process mining and RPA, we draw on a structured literature review and design science research to reveal and operationalize organizational practices and capabilities as well as process- and technology-specific socio-technical antecedents that are fundamental for the successful adoption of business process technology. Second, taking the examples of process mining and RPA, we employ case studies and design science research to show how novel business process technology influences the goals and practices of organizational BPM. Third, taking the example of process mining and DLT, we employ case studies and design science research to shed light on how organizations achieve awareness and redesign of their business processes through leveraging novel business process technology. The findings build on empirical data from 68 interviews and 51 files of secondary data.

Results: This dissertation reveals how organizations adopt and implement novel business process technologies and how their use presents organizations with opportunities for achieving new approaches to and outcomes of BPM. As a result, we show three shifts in BPM that are currently unfolding, driven by the emergence of novel digital business process technologies. First, we demonstrate that facilitated by the capabilities of novel business process technology, the adoption of BPM practices in organizations shifts from a formerly centralized to a democratized approach. However, this democratized approach also poses new challenges and complexities to organizations, thus, requiring them to provide necessary antecedents to ensure successful adoption. Second, we highlight that through the democratized, bottom-up-driven use of novel business process technology in organizations, the goals of their BPM practices shift from centrally controlling the adherence to pre-defined processes to also enabling dynamic, decentralized process innovation. Third, we find that novel business process technology allows organizations not only to understand and redesign processes within their organizational boundaries at the intra-organizational level but also end-to-end processes across organizational boundaries at the inter-organizational level.

Contribution: The findings of this dissertation contribute to the literature on business process technology and BPM threefold. First, we contribute to research on the organizational adoption of business process technology by synthesizing and operationalizing antecedents for adopting novel diagnostic and automating business process technologies while highlighting potential challenges. Second, we contribute to research on organizational value realization from business process technology by shedding light on the underlying mechanisms of how organizations implement and benefit from novel diagnostic and automating business process technologies. Third, we contribute to research on BPM in the digital era by revealing how BPM practices change when organizations leverage novel diagnostic and automating business process technology and how these practices result in unprecedented opportunities for process transformation. Furthermore, we provide practical implications for organizations to tackle the challenges of adopting novel business process technology and guidance on how, when, and why to use these technologies to advance and improve their BPM practices.

Limitations: This dissertation is subject to several limitations grounded in our choice of research paradigm, research methods, and data sources. First, limitations regarding the validity and generalization of our findings emerge from our adopted constructivist research paradigm, which is based on a relativist ontology and a subjectivist epistemology. Second, we acknowledge the limitations of comprehensiveness and theoretical bias pertaining to the literature reviews we conducted in our research. Third, we point toward the limitations of the case studies we conducted concerning their construct validity, internal validity, external validity, and reliability. Fourth, we recognize limitations in relation to the design science research we conducted that are grounded in the chosen data sources from literature and practice and the executed evaluation methods.

Future Research: This dissertation opens up three promising avenues for future research. First, we encourage scholars to utilize the knowledge we generated on antecedents for adopting business process technology to shed light on the development of and the social, ethical, and legal challenges related to these antecedents. For example, there is still only sparse knowledge on how organizations can develop these antecedents, such as designing IS governance mechanisms that support process data generation, and how organizations can address emerging challenges, such as backlashes against transparency and automation of work. Second, we call for future research to leverage our findings on business process technology use and its implications on BPM practices to generate deeper insights into how organizations can manage these novel usage patterns and shifting BPM practices. For example, scholars need to understand how organizations can manage the interrelations between the decentralized adoption of novel business process technology and the centralized use of traditional business process technology. Third, we call for future research to utilize the knowledge we generated on the effects of using novel business process technology on process awareness and redesign. For example, socio-technical challenges concerning inter-organizational process awareness, such as process data sharing, remain to be addressed.

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List of Abbreviations

AMCIS	Americas Conference on Information Systems
API	Application Programming Interface
BDA	Big Data Analytics
BISE	Business & Information Systems Engineering
BPM	Business Process Management
BPR	Business Process Reengineering
CON	Conference
DD	Due Diligence
DLT	Distributed Ledger Technology
ECIS	European Conference on Information Systems
ERP	Enterprise Resource Planning
HICSS	Hawaii International Conference on System Sciences
IoT	Internet of Things
IS	Information System
IT	Information Technology
IT DD	Information Technology Due Diligence
JN	Journal
KPI	Key Performance Indicator
M&A	Mergers & Acquisitions
NR	Not Ranked
P	Publication
PACIS	Pacific Asia Conference on Information Systems
RPA	Robotic Process Automation
RQ	Research Question
SME	Subject Matter Expert
VHB	Verband der Hochschullehrer für Betriebswirtschaft
WfMS	Workflow Management System

Part A

1 Introduction

"Without continual growth and progress, such words as improvement, achievement, and success have no meaning." (Benjamin Franklin)[1]

The improvement of business processes is inextricably interwoven with the concept of modern organizations and, thus, poses an enduring challenge that has and, most likely, always will engage organizations. Achieving efficient and effective business processes that contribute to organizational success has been a foundational topic to research on business process management (BPM) for decades (Dumas et al., 2013; Grover & Markus, 2008). However, neither organizations nor their business processes are static phenomena. Instead, they are constantly changing just as their environment changes and progresses. In recent years, digital transformation has presented a particularly dynamic environment to organizations full of transformative forces, which challenges long-held assumptions of BPM while simultaneously offering new technological opportunities for BPM. Consequently, the question emerges of how organizations can achieve process management and improvement under the new paradigm of digital transformation (Baiyere et al., 2020). However, as Benjamin Franklin famously expressed, improvement and success have no meaning without underlying growth and progress. Therefore, we need to understand how the discipline of BPM can progress by leveraging new technological advancements and how this progress might change the notion of improving business processes in the digital age.

1.1 Motivation

In recent years, organizations have been challenged to manage their business processes in the increasingly dynamic and complex context of digital transformation (Baiyere et al., 2020). In particular, digital transformation involves the transformation of business operations, products, and processes through leveraging digital technologies (Riasanow et al., 2019). For example, big data analytics (BDA) and artificial intelligence fundamentally change decision-making processes in organizations (Günther et al., 2017), while Internet-of-Things (IoT) technology ushers in a new era in industries such as services and manufacturing (Kalsoom et al., 2021). As a result, digital transformation leads to a continuously changing environment that undergoes frequent structural and operational shifts, which requires organizations to ensure efficient and adaptive business processes (Davenport, 2006; Hammer & Stanton, 1999; Hrabal et al., 2020). While the design and management of business processes have a long-standing tradition in research on BPM, the new context of digitally transforming organizations and industries challenges the assumptions that traditionally underlie BPM (vom Brocke et al., 2016), in particular, a stable context (Baiyere et al., 2020) and the supporting role of information systems (IS) (Sidorova et al., 2015). Instead, practice shows that the digital transformation of organizations can lead to fast context changes, for example, as new digital offerings and digital marketplaces transform processes in brick-and-mortar retail (Böttcher et al., 2021). Additionally, we observe a change in the role of IS to not only support but enable new business

[1] As cited in Atkinson (2019).

processes, for example, as organizations use IoT technologies to achieve predictive maintenance of machines (Kalsoom et al., 2021).

Informed by these changes and digital transformation itself, novel technologies have emerged to facilitate the management of business processes (Kerpedzhiev et al., 2021; Sidorova et al., 2015). These technologies fall into the category of business process technology which comprises "*tools to analyze, document, specify, monitor, simulate, support and implement business processes*" (Draheim, 2010, p. 4). While traditional business process technologies, such as Workflow Management Systems (WfMS) and BPM suites, have been the focus of research and practice for decades (Sidorova et al., 2015), in recent years, novel technologies have developed that offer new opportunities for BPM and the digital transformation of business processes (Mendling et al., 2020). In particular, we observe two salient developments that unfold in the fields of diagnostic and automating business process technology.

First, organizations nowadays can access vast amounts of heterogeneous process data that originate at high velocity from various sources inside and outside the firm (Abbasi et al., 2016; Kirchmer, 2021; van der Aalst, 2016). This becomes evident, for example, in the way every business department today is supported by a variety of IS that are used by users with different goals, experiences, and habits, which creates a wealth of process data. Organizations, thus, strive to integrate, pre-process and analyze these rich process data to generate unprecedented knowledge illuminating processes on the inside and outside of the organization and fostering process change enabled by information technology (IT) (Davenport, 2006; Jurisch, 2014). To this end, diagnostic business process technologies have experienced an upswing in recent years, with process mining being one of the most prominent examples (Choudhary et al., 2021). Process mining is a BDA technology that aims to discover, monitor, and improve business processes by analyzing large amounts of process data readily available in today's information systems (Baader, 2019; van der Aalst, 2011). Consequently, organizations increasingly use process mining to create continuous transparency of their end-to-end business processes as the foundation for process management and improvements (Grisold et al., 2020).

Second, with the recent emergence of new development paradigms, such as low code development (Bock & Frank, 2021), and new implementation approaches, such as distributed ledger technology (DLT) for decentralized data storage (El Ioini & Pahl, 2018), organizations can now achieve fast and scalable automation of business processes that was previously not feasible. For example, robotic process automation (RPA), a digital technology for business process automation, has attracted attention from organizations across industries for automating tedious, repetitive manual tasks (Hofmann et al., 2020). RPA consists of software bots that provide an "*infinitely scalable virtual human*" as they are programmed to process structured input data on the interface of existing IS at the speed of a machine (Willcocks & Lacity, 2016). Since RPA is often based on a low code approach, not only professional developers but particularly the operational workforce without an IT background can implement process automation, thereby offering scalability (Osmundsen et al., 2019).

In sum, nowadays, organizations are provided with novel opportunities for analyzing, managing, and automating their business processes based on recent developments in diagnostic and automating business process technology. Their rapid gain in practical relevance reflects the importance of these technologies. For example, the market volume of process mining has increased enormously and is expected to reach $2.3 billion by 2025, with a growth rate of around 33% per year (Biscotti et al., 2021), while the RPA market currently values at $2.3 billion and is expected to grow by about 40% per year until 2030 (Grand View Research, 2023). These practical insights illustrate how the entanglement of BPM and digital transformation leads organizations to choose novel technology-driven pathways to transform their business processes (Mendling et al., 2020).

However, practice also shows that organizations face multiple challenges when leveraging novel business process technologies to transform their processes. These challenges are not only technological, such as the necessary infrastructure to profit from new automating business process technologies (Syed, Suriadi, et al., 2020) or strategies to deal with heterogeneity and varying quality of process data to benefit from new diagnostic business process technologies (Baesens et al., 2016), but also encompass a socio-technical dimension. For example, a recent report from Germany indicates that although 80% of the surveyed organizations foster the use of process mining, they still do not realize the technology's full potential and face unanswered questions regarding collaboration, utilization, and implementation strategies (Reder et al., 2019). Similarly, reports point toward 30%-50% failure rates of RPA projects due to socio-technical challenges in the implementation, maintenance, and use of the technology (Ernst & Young, 2016; Noppen et al., 2020). These challenges are exacerbated as the use of business process technologies unfolds as a multi-layered phenomenon that affects both the individual user and the organization and its processes and, thus, places high demands on the socio-technical context within which the technologies are used. However, we lack answers to address these challenges. In particular, we need to understand the antecedents for organizations to adopt these novel business process technologies, how these technologies enable new approaches to BPM, and how, as a result, organizations can transform their business processes. This current lack of knowledge is reflected in three gaps in the literature.

First, research on diagnostic and automating business process technologies lacks a systematic understanding of the organizational antecedents necessary to adopt these technologies. Taking the example of process mining and RPA, we observe that to date, both literature streams have primarily focused on technical factors enabling organizational adoption (Syed, Suriadi, et al., 2020; Thiede et al., 2018), such as the necessary data quality for process diagnosis (van der Aalst et al., 2012) or the technical infrastructure for process automation (Issac et al., 2018). In contrast, socio-technical antecedents, such as required organizational structures and practices, have remained largely unaddressed (Badakhshan et al., 2022; Grisold et al., 2020). For example, only recently has there been a shift in process mining research toward addressing socio-technical questions (Badakhshan et al., 2022), such as factors influencing the selection of process mining use cases (Rott & Böhm, 2022) and success factors for process mining use in organizations (Mans et al., 2013). These studies provide a valuable starting point by shedding light on the socio-technical factors influencing the adoption, implementation, and benefits of process mining use. However, knowledge in the field is still fragmented and lacks a systematic understanding which limits our understanding of how organizations can ensure to successfully introduce and integrate these technologies (Badakhshan et al., 2022; Grisold et al., 2020).

Second, there is a lack of knowledge on how using novel diagnostic and automating business process technology influences organizations' BPM goals and practices (Baiyere et al., 2020; Mendling et al., 2020). Due to their interpretive flexibility (Engert et al., 2021) and emerging development paradigms based on low code (Bock & Frank, 2021), novel business process technologies can be used for different reasons and in different ways compared to traditional BPM technologies (Badakhshan et al., 2022; Mendling et al., 2020). For example, organizations face new options for structuring the implementation and use of novel business process technologies, such as process mining and RPA, by offering access to these technologies to the entire organization and not only to process or IT professionals. As a result, new avenues for BPM might open up, for example, as not only process and IT professionals but also operational employees become engaged in process improvement activities (vom Brocke et al., 2021). However, thus far, research is dominated by the focus on using traditional business process technologies, such as BPMS or Enterprise Resource Planning (ERP) systems, for supporting BPM (Ahmad & van Looy, 2019). In contrast, the use of novel diagnostic and automating business process technologies in the context of BPM has largely remained unaddressed, leaving it unclear how organizations use these technologies and how they influence their BPM practices (Grisold et al., 2020; Osmundsen et al., 2019; vom Brocke et al., 2021).

Third, there is currently a disconnect between research about novel diagnostic and automating business process technologies and research on realizing business process transformation (Baiyere et al., 2020; Mendling et al., 2020). As a result, even though we have an understanding of the availability and use case scenarios of novel business process technologies (Syed, Suriadi, et al., 2020; Thiede et al., 2018), we still do not know how their use affects the transformation of business processes. For example, the literature on BPM indicates that understanding and being aware of end-to-end business processes are crucial antecedents for changing end-to-end processes (Dumas et al., 2013). Nevertheless, we do not know how novel business process technologies, such as process mining, influence the development of organizational process awareness. Similarly, even though research indicates that automating business process technologies such as DLT and smart contracts offer new use case scenarios for process automation (El Ioini & Pahl, 2018), we lack an understanding of how they enable new process designs (Cai et al., 2019). Consequently, our knowledge is limited on how diagnostic and automating business process technologies impact organizational awareness and redesign of business processes.

1.2 Research Questions

This dissertation is motivated by the observation that, in the era of digital transformation, organizations face the challenge of managing business processes in an increasingly dynamic and complex environment. To this end, novel diagnostic and automating business process technologies have emerged to support BPM, offering organizations unprecedented business process transparency and automation capabilities. However, organizations still struggle to leverage these technologies. In particular, organizations need to understand the antecedents necessary to adopt these technologies, how these technologies enable new approaches to BPM, and how, as a result, organizations can transform their business processes.

Acknowledging the variety of business process technologies available in recent years, this dissertation intentionally emphasizes diagnostic and automating business process technologies as two technology categories of increasing importance in contemporary organizations.

To address the outlined gaps, this dissertation draws on an empirically driven research design that builds on literature on diagnostic and automating business process technologies in combination with qualitative data[2] from multiple organizational cases leveraging business process technology.

RQ1: *What are socio-technical antecedents for the organizational adoption of novel business process technology?*

Understanding the implications of business process technologies on BPM practices and the transformation of business processes first requires a systematic understanding of the antecedents necessary for organizations to adopt these technologies. Adoption refers to the process of introducing and integrating technology in an organization (Thong, 2015). Taking the example of diagnostic and automating business process technologies, we observe that to date, both literature streams have primarily focused on technical factors enabling adoption, such as the necessary data quality for process diagnosis (van der Aalst et al., 2012) or the technical infrastructure for process automation (Issac et al., 2018). In contrast, socio-technical antecedents, such as required organizational structures, practices, and governance approaches, have, despite their well-established importance for successful IS implementation (Poon & Wagner, 2001), remained largely unaddressed (Badakhshan et al., 2022; Grisold et al., 2020). To shed light on these socio-technical antecedents, in the first research question, we set out to study process mining as an example of diagnostic business process technology and RPA as an instance of automating business process technology in the context of organizational adoption.

First, taking process mining as the contemporary diagnostic process technology of the highest relevance (Kerremans, 2019), we set out to contextualize process mining as an IT artifact used in organizations. Following the methodological guideline of an assessing literature review (Leidner, 2018) and drawing on a grounded theory coding procedure (Glaser & Strauss, 1967), we synthesize the findings of 58 empirical studies to describe socio-technical antecedents, in particular organizational capabilities and practices, that enable organizations to adopt process mining. In addition, we corroborate and extend these findings by adopting a design science approach (Hevner, 2007) to develop a structured framework for assessing antecedents and expected value potentials of process mining based on the taxonomy development method proposed by Nickerson et al. (2013). Second, we focus on socio-technical antecedents for adopting RPA as a promising new means of automating business process technology. Drawing on literature and the results of a case study (Yin, 2014) of an automotive organization adopting RPA, we shed light on socio-technical challenges that organizations experience when adopting RPA and how addressing those challenges can help organizations to establish the foundation for RPA.

[2] We provide an overview of all the qualitative data used in the embedded publications in Appendix A: Supplementary Material: Interviews and Archival Data.

RQ2: *How does the use of novel business process technology influence the goals and practices of business process management?*

With the second research question, we shift the focus from the adoption of business process technology to its implications on the goals and practices of BPM in organizations.

Due to their flexibility in interpretation (Engert et al., 2021) and development based on low code (Bock & Frank, 2021), novel business process technologies, including process mining and RPA, can be adopted and governed in ways that differ from traditional BPM technologies (Badakhshan et al., 2022; Mendling et al., 2020). For instance, organizations now have various options for structuring the implementation and usage of these technologies, such as extending access to them beyond process or IT professionals to the entire organization. Consequently, new possibilities arise in BPM, as not only process and IT professionals but also operational employees become involved in process improvement activities (vom Brocke et al., 2021). However, existing research predominantly focuses on the implications of traditional business process technologies like WfMS or Enterprise Resource Planning (ERP) systems for BPM purposes. In contrast, the utilization of novel diagnostic and automating business process technologies in BPM remains largely unexplored, leaving uncertainties regarding how organizations employ these novel technologies and how they impact BPM practices (Grisold et al., 2020; Osmundsen et al., 2019; vom Brocke et al., 2021).

First, taking process mining as an example of diagnostic business process technology, we reveal two distinct governance approaches for process mining, top-down- and bottom-up-driven governance, and study how process mining use under each governance approach influences the organizations' BPM practices. To this end, we conduct a multiple case study (Yin, 2014) drawing on data from 24 semi-structured interviews and archival sources that identifies seven usage patterns for process mining that depend on the chosen governance approach and yield different effects for the organizations' BPM practices. Second, we chose to study RPA as an automating business process technology that promises scalable automation through decentralized governance and implementation (Osmundsen et al., 2019). We build on empirical data and the results of a design science research approach (Hevner, 2007) at an automotive firm implementing RPA to provide insights into how organizations can manage the decentralized governance of RPA and its effects on structures, roles, and practices related to business process automation.

RQ3: *What are the implications of using novel business process technology on organizational awareness about and redesign of business processes?*

The third research question shifts the focus from studying the use of business process technology for BPM to understanding its outcomes for organizations, particularly concerning the transformation of business processes. Previous research indicates that using novel business process technologies allows organizations to continuously analyze and improve business processes (Baiyere et al., 2020; Mendling et al., 2020). For example, first studies point towards the potential of diagnostic business process technologies, such as process mining, to provide unmatched process transparency for organizations (Grisold et al., 2020), while scholars in the field of automating business process technologies, such as DLT, draw our attention towards opportunities for novel technology-enabled process designs (Nzuva, 2019; Wang et al., 2019)). However, there is still only sparse knowledge on how the use of these technologies affects the transformation and change of business processes (Badakhshan et al., 2022). For example, we lack knowledge of how the transparency created through process mining influences organizational awareness of business processes (Grisold et al., 2020) or how the use of DLT facilitates novel process designs (Cai et al., 2019). Therefore, in the third research question, we set out to unravel the effects of diagnostic and automating business process technologies on the transformation of business processes.

First, revisiting the example of process mining as diagnostic business process technology, we show how organizations achieve increased process awareness by using process mining. Employing a multiple case study of four organizations, this study reveals seven socio-technical mechanisms based on process mining that enable organizations to create an either standardized or shared awareness of subprocesses, end-to-end processes, and the firm’s process landscape. In addition, we corroborate and extend these findings in the inter-organizational context by conducting a design science research approach to develop process mining analyses for achieving process awareness in the inter-organizational context of mergers & acquisitions (M&A). Second, taking the example of smart contracts based on blockchains as automation technology, we unravel how organizations use the technology to redesign and automate their processes. By conducting an exploratory case study (Yin, 2014) of four start-ups, we analyze the business process automation potentials that organizations can gain through smart contracts and how this automation approach differs from existing automation technologies, such as WfMS and ERP systems.

In sum, we adopt a socio-technical perspective, which is at the heart of the IS discipline (Sarker et al., 2019), in shifting research from the predominant focus on traditional technologies for BPM support to novel business process technology. As a result, this allows us to study how organizations can adopt novel diagnostic and automating business process technology, how these technologies enable new approaches to BPM, and how, as a result, organizations can transform their business processes.

1.3 Structure

This publication-based dissertation consists of three parts A, B, and C (see Figure 1). Part A first motivates the research field of BPM in the context of digital transformation, followed by the introduction of the three research questions and an overview of the structure of this dissertation (see Part A: Chapter 1). Next, we provide the conceptual background on business processes, then synthesize the literature on BPM and business process transformation (including process awareness and process redesign), and explain the fundamentals of business process technology (including process mining, RPA, DLT, and smart contracts). We conclude Part A by introducing our research design, which comprises the research paradigm, including ontological and epistemological assumptions, the qualitative research strategy, and the research methods employed (see Part A: Chapter 3).

Figure 1. Structure of the dissertation (own illustration)
(Publications with an asterisk (*) provide results on multiple research questions)

Part A

Introduction, conceptual background, research strategy

Part B

Socio-technical antecedents for the organizational adoption of business process technology

RQ1: What are socio-technical antecedents for the organizational adoption of novel business process technology?

Diagnostic business process technology:

P1: Turning Big Data into Value: A Literature Review on Business Value Realization from Process Mining

Method: Structured literature review

P5: Assessing Process Mining Use Cases: A Taxonomy of Antecedents and Value Potentials of Process Mining

Method: Taxonomy development

Automating business process technology:

P4*: Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development

Method: Design science research

Novel approaches to business process management enabled by business process technology use

RQ2: How does the use of novel business process technology influence the goals and practices of business process management?

Diagnostic business process technology:

P2*: No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness

Method: Case study research

Automating business process technology:

P4*: Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development

Method: Design science research

Transformation of business processes as an outcome of business process technology use

RQ3: What are the implications of using novel business process technology on organizational awareness about and redesign of business processes?

Diagnostic business process technology:

P2*: No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness

Method: Case study research

P6: Leveraging Big Data for M&A: Towards Designing Process Mining Analyses for Process Assessment in IT Due Diligence

Method: Design science research

Automating business process technology:

P3: Process Automation on the Blockchain: An Exploratory Case Study on Smart Contracts

Method: Case study research

Part C

Summary of results, discussion, implications for theory and practice, limitations, future research and conclusion

Part B provides information on our six main published and peer-reviewed publications (P) related to the three research questions. It is to be noted that some publications provide results in relation to multiple research questions. First, concerning RQ1, publications **P1**, **P4**, and **P5** provide findings derived from the literature and empirical data on socio-technical antecedents for the organizational adoption of diagnostic and automating business process technology, respectively (see Part B: Chapter 4, 7 and 8). Then, addressing RQ2, publications **P2** and **P4** highlight how the governance and use of diagnostic and automating business process technology, respectively, enable new BPM practices (see Part B: Chapter 5 and 7). Last, in relation to RQ3, publications **P2**, **P3**, and **P6** provide insights into the implications of the organizational use of diagnostic and automating business process technology, respectively (see Part B: Chapter 5, 6, and 9), on the transformation of business processes.

In Part C, we begin by providing a summary of the findings from the six embedded papers (see Part C: Chapter 10). Furthermore, we discuss the results of the articles (see Part C: Chapter 11), highlight theoretical and practical implications (see Part C: Chapter 12), acknowledge the limitations of this dissertation (see Part C: Chapter 13), outline potential avenues for future research (see Part C: Chapter 14), and end with a conclusion of this dissertation (see Part C: Chapter 15).

Table 1. Overview of publications embedded in this dissertation

#	Authors	Title	Outlet	Type (Ranking)	RQ
P1	Eggers, J. Hein, A.	Turning Big Data into Value: A Literature Review on Business Value Realization from Process Mining	ECIS* 2020	CON (VHB: B)	RQ1
P2	Eggers, J. Hein, A. Böhm, M. Krcmar, H.	No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness	BISE* 2021	JNL (VHB: B)	RQ2, RQ3
P3	Eggers, J. Hein, A. Weking, J. Böhm, M. Krcmar, H.	Process Automation on the Blockchain: An Exploratory Case Study on Smart Contracts	HICSS* 2021	CON (VHB: C)	RQ3
P4	Eggers, J. Wewerka, J. Viljoen, A. Krcmar, H.	Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development	HICSS* 2023	CON (VHB: C)	RQ1, RQ2
P5	Eggers, J. Häge, M.-C. Zimmermann, S. Gewald, H.	Assessing Process Mining Use Cases: A Taxonomy of Antecedents and Value Potentials of Process Mining	AMCIS* 2023	CON (VHB: D)	RQ1
P6	Eggers, J. Hein, A. Böhm, M. Krcmar, H.	Leveraging Big Data for M&A: Towards Designing Process Mining Analyses for Process Assessment in IT Due Diligence	PACIS* 2023	CON (VHB: C)	RQ3

Outlet:
AMCIS Americas Conference on Information Systems
BISE Business & Information Systems Engineering
ECIS European Conference on Information Systems
HICSS Hawaii International Conference on System Sciences
PACIS Pacific Asia Conference on Information Systems

Type:
CON Conference
JNL Journal
VHB German Academic Association for Business Research

*Publication is published and peer-reviewed.

In the following, we give an overview of the publications embedded in this dissertation (see Table 1) and an overview of additional publications (see Table 2). Furthermore, we describe the addressed research problem, the methodological approach, and the key contributions of the six publications embedded in Part B.

P1: Turning Big Data into Value: A Literature Review on Business Value Realization from Process Mining. The first publication (Eggers & Hein, 2020) sheds light on how organizations realize value potentials by using process mining as the leading BDA technology for business process analysis. By extracting knowledge from event logs readily available in information systems, process mining provides new ways to discover, monitor, and improve processes while being agnostic to the source system. Despite its undisputed practical relevance, research yields only a limited understanding of how organizations realize value potentials from applying process mining in different organizational contexts. Addressing this gap, the article conducts an assessing literature review by analyzing 58 papers from the literature on process mining to synthesize the existing knowledge on business value realization from process mining. The analysis is guided by adopting the perspective of process mining embedded within its organizational context. By analyzing the dimensions of the nomological net around process mining, this study contributes twofold to the broader research field of BDA value realization. The article, first, uncovers which benefits organizations gain by applying process mining and, second, demonstrates the organizational capabilities and practices that influence how organizations use and implement process mining. In addition, the study reveals how process mining leads to business value realization and, based on these results, suggests directions for future research on process mining in the organizational context.

P2: No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness. The second article (Eggers, Hein, Böhm, et al., 2021) investigates how organizations leverage the process transparency introduced by process mining to increase their process awareness. Even though process mining provides unprecedented transparency of business processes, there is still a limited understanding of how organizations act upon this transparency and how they leverage it to benefit from increased process awareness. Addressing this gap, this study conducts a multiple case study to explore how four organizations achieved increased process awareness by using process mining. Drawing on data from 24 semi-structured interviews and archival sources, this study reveals seven socio-technical mechanisms based on process mining that enable organizations to create an either standardized or shared awareness of subprocesses, end-to-end processes, and the firm's process landscape. This study contributes to research on BPM by revealing how process mining facilitates mechanisms that serve as a new, data-driven way of creating process awareness. In addition, the findings indicate that these mechanisms are influenced by the governance approach chosen to conduct process mining, i.e., a top-down or bottom-up driven implementation approach. Last, this study also points to the importance of balancing the social complications of increased process transparency and awareness. These results serve as a valuable starting point for practitioners to reflect on measures to increase organizational process awareness through process mining.

P3: Process Automation on the Blockchain: An Exploratory Case Study on Smart Contracts. The third publication (Eggers, Hein, Weking, et al., 2021) analyzes the potential for business process automation that organizations achieve through smart contracts. While business process automation through IT has progressed over the last decades, smart contracts have recently emerged as a promising new means of automation. However, in practice, the adoption of smart contract-based automation is still low, raising the question if the technology genuinely offers a unique approach to process automation. This study draws on an exploratory case study of four start-ups to investigate the automation potential that organizations achieve through smart contracts and how smart contracts differ from established automation technologies, such as WfMS, ERP systems, and RPA. Hence, the article contributes to the literature on process automation by unveiling automation by disintermediation and automation by reducing manual process steps as two outcomes of applying smart contracts. The study further discusses the characteristics of smart contracts that differentiate them from established automation technologies. Besides, the study provides practitioners with an understanding of application scenarios, potentials, and drawbacks of smart contracts for process automation.

P4: Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development. The fourth publication (Eggers, Wewerka, et al., 2023) derives a software development framework for guiding the realization of decentralized RPA projects. RPA has emerged as a promising automation technology in recent years. Firms seize RPA for fast and cost-efficient low code process automation implemented and maintained decentrally in the business units by subject matter experts (SMEs) without IT development experience. However, decentralized RPA projects are reported to frequently fail and be prone to challenges as SMEs struggle to meet their new roles and responsibilities, such as developers or testers. Yet, research lacks an understanding of how challenges related to SMEs' roles and responsibilities unfold and how to address these challenges when executing decentralized RPA projects. To this end, this study employs a design science research approach, drawing on literature and 14 expert interviews, to (1) systematically synthesize the challenges related to SMEs' roles and responsibilities and (2) derive a software development framework for supporting SMEs in their new roles and responsibilities in decentralized RPA projects. Thus, this study contributes to RPA and low code development research and provides SMEs with guidelines to navigate decentralized RPA projects in practice.

P5: Assessing Process Mining Use Cases: A Taxonomy of Antecedents and Value Potentials of Process Mining. The fifth publication (Eggers, Häge, et al., 2023) develops a structured framework for assessing the cost-benefit ratio of process mining use cases based on their antecedents and expected value potentials. Even though process mining has become increasingly popular in discovering, monitoring, and enhancing business processes, organizations still face challenges in effectively implementing and deriving value from process mining. First, organizations struggle to identify and establish the necessary antecedents for implementing process mining use cases, and second, there is a lack of guidance in identifying and evaluating valuable process mining use cases. Because knowledge in this field remains fragmented thus far, there is no comprehensive understanding of how organizations can assess antecedents and value potentials to identify valuable process mining use cases. To address this gap, this study adopts a design science research approach and develops a structured framework based on the taxonomy development method proposed by Nickerson et al. (2013). This framework allows assessing process mining use cases by considering their antecedents and expected value potentials. Through an iterative process, this study develops and evaluates the taxonomy by drawing on existing process mining literature and related research fields and conducting twelve semi-structured interviews at a German manufacturing corporation. As a result, our study contributes to research on the implementation and utilization of process mining, providing researchers and practitioners with a better understanding of the factors that influence the selection of process mining use cases and a practical tool for assessing them.

P6: Leveraging Big Data for M&A: Towards Designing Process Mining Analyses for Process Assessment in IT Due Diligence. The sixth publication (Eggers, Hein, et al., 2023) operationalizes and implements process mining analyses for process assessment conducted during IT due diligence (IT DD) in the context of M&A. The success of M&A hinges on the buyer's thorough evaluation of the target firm and its fit to the buyer, known as due diligence (DD). In recent times, assessing the target's IT-enabled processes has emerged as a new responsibility in IT DD. However, there is still a lack of knowledge about how to design and execute the process assessment in IT DD. Addressing this challenge, this study proposes the utilization of process mining to conduct process assessment in IT DD and enable the analysis and comparison of the buyer's and target's IT-enabled processes. Through a design science research approach, this study draws on existing literature and 12 interviews to uncover and operationalize the requirements for process assessment in IT DD. We demonstrate how process mining can be used to measure these operationalized requirements and extract design principles and enabling factors that can guide the design, implementation, and use of process mining for process assessment in IT DD. As a result, our study makes valuable contributions to the research fields of IT DD, M&A, and process mining, providing practitioners with important design knowledge and a prototypical process mining tool to effectively employ process mining in the process assessment of IT DD.

In addition to the key publications **P1-P6**, this dissertation also points to three publications (see Table 2) that are tangentially related to our three research questions (see Chapter 1.2). While publications **P1-P6** provide the central results of this dissertation, **P7-P9** shed light on extended insights into the application of diagnostic and automating business process technology in organizations.

Related to RQ1 and RQ3, **P7** provides insights into the antecedents for and value potentials of applying process mining in the context of the aviation industry.

Related to RQ3, **P8** sheds light on how the use of process mining enables firms to create shared end-to-end process awareness through technology-enabled organizational learning.

Related to RQ2 and RQ3, **P9** reveals how the decentralized low code implementation of RPA leads to the conscious articulation of tacit process knowledge.

Table 2. Overview of additional publications

#	Authors	Title	Outlet	Type (Ranking)
P7	Böhm, M. Rott, J. Eggers, J. Grindemann, P. Nakladal, J. Hoffmann, M. Krcmar, H.	Process mining at Lufthansa CityLine: The path to process excellence	JIT TC*	JNL (VHB: NR)
P8	Eggers, J. Hein, A. Krcmar, H.	Bridging the Gap: How Firms Use Process Mining to Create and Act on a Shared End-to-End Process Understanding	Under Review at ICIS 2023	CON (VHB: A)
P9	Eggers, J. Hein, A. Krcmar, H.	Sharing the Unconscious: An Exploration of Tacit Knowledge Articulation During Robotic Process Automation Low Code Development	Under Review at ISR	JNL (VHB: A+)

Outlet:
ICIS International Conference on Information Systems
ISR Information Systems Research
JIT TC Journal of Information Technology Teaching Cases

Type:
CON Conference
JNL Journal
VHB German Academic Association for Business Research
NR Not ranked

*Publication is published and peer-reviewed.

2 Conceptual Background

The following chapter consolidates findings from several research streams to provide the conceptual background for the primary phenomenon of this dissertation— the organizational use of novel business process technology and its implications on BPM. To this end, we synthesize the literature on business processes and process orientation, outline key concepts of BPM and the transformation of business processes, and conclude with a summary of the underlying concepts and organizational use of recent diagnostic and automating business process technologies.

2.1 Business Processes and Process Orientation

2.1.1 Business Processes

Dating back to the ideas of Adam Smith (Smith, 1776) and later Frederick W. Taylor (Taylor, 1919) about the division of labor and standardization of work methods, business processes are a phenomenon that has long been studied in various research fields, ranging from engineering research over organizational research to IS research (Davenport & Short, 1990; Dumas et al., 2013; Grover & Markus, 2008). As a result, research has not yielded a uniform definition of business processes but instead has employed different approaches to conceptualizing business processes[3]. Thus, drawing on the fields of BPM and IS research, we give an overview of the most commonly cited definitions (see Table 3).

Table 3. Business process definitions from the fields of BPM and IS research

Source	Definition
Davenport and Short (1990)	We define business processes as a set of logically-related tasks performed to achieve a defined business outcome. This is similar to Pall's definition of process as "the logical organization of people, materials, energy, equipment, and procedures into work activities designed to produce a specified end result (work product)."
Dumas et al. (2013)	[…] we define a business process as a collection of inter-related events, activities, and decision points that involve a number of actors and objects, which collectively lead to an outcome that is of value to at least one customer.
Hammer and Champy (1993)	We define a business process as a collection of activities that takes one or more kinds of input and creates an output that is of value to the customer.

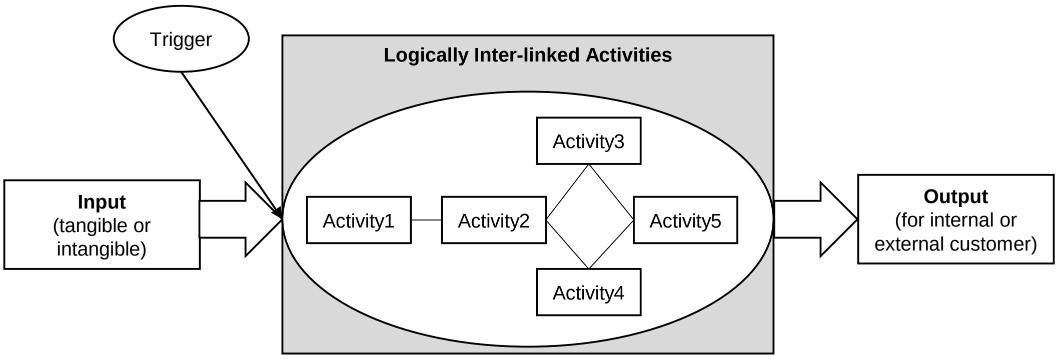
[3] Although the terms *business process* and *process* do not necessarily refer to the same phenomenon, especially since a business process refers to a process in an organizational context while a process can refer to any set of interrelated activities, including, for example, in a private or social context, the terms are used interchangeably in the business process literature (Dumas et al., 2013; vom Brocke & Roseman, 2015). Therefore, in the context of this dissertation, we adhere to common practice and use the terms *business process* and *process* interchangeably to refer to processes in an organizational context.

Lee and Dale (1998)	Indeed, business processes can be considered the "strands of activity that link the operations of an organisation to the requirements of its customers" (IMI, 1994). They are generally cross-functional, horizontal in nature, lie outside the usual vertical, hierarchical company structure, and no single person has responsibility for the entire process.
Scheer (1999)	A business process is a continuous series of enterprise tasks, undertaken for the purpose of creating output. The starting point and final output of the business process is the output requested and utilized by corporate or external "customers".
Schwarzer and Krcmar (2014)	In a process, an object that enters the process as input is changed by various machine or human activities (transformation). As a result, the object is transformed into a specific state in which it leaves the process again as output.
Talwar (1993)	[…] a process will be taken to be any sequence of pre-defined activities executed to achieve a pre-specified type or range of outcomes.

From the overview of definitions, emerge commonalities in terms of the purpose, structure, and actors involved in a business process. First, business processes are directed at creating a (pre-) specified **output** that is of value to a corporate, thus, internal, or an external customer (Davenport & Short, 1990; Scheer, 1999), for example, a manufactured product that is handed to the warehouse department. Second, a business process is triggered by one or more intangible or tangible **inputs**—this can also be referred to as an event (Dumas et al., 2013)— for example, the arrival of materials at a production plant, which is **transformed** through a series of logically interlinked, specified **activities** to create the specified output (Hammer & Champy, 1993; Talwar, 1993). Third, a business process is not executed by one single actor but instead spans several **organizational functions** that coordinate their specialized efforts to create the desired output (Lee & Dale, 1998). Consequently, the output of one process is often the input of another process (Dumas et al., 2013). For example, an order processed by the sales department serves as input for the production department to produce the desired product, as is the finished product released by the production department, the input for the warehouse department to ship the product to the customer. Figure 2 illustrates the conceptual foundation of business processes.

The **horizontal** understanding of business processes often stands in contrast to the **vertical** structure of organizations. Based on the concept of division of labor, organizations usually structure their work along functional departments, such as marketing, sales, or production, so that each department fulfills a specific portion of the organization's value-creation processes (Hammer & Champy, 1993). Consequently, business processes can be conceived (and managed) at different organizational levels. On the lowest level of abstraction, organizations can consider their processes on the **inter-individual level**, which refers to sub-processes that are carried out within small workgroups or functional departments. In this context, each sub-process represents a "*self-contained, composite activity that can be broken down into smaller units of work*" (Dumas et al., 2013, p. 102). However, if organizations focus only on their sub-processes, they risk thinking about and optimizing functional silos while overlooking the potential of realizing cross-functional improvements (Lee & Dale, 1998). Drawing on this observation, in their seminal article on process orientation, Davenport and Short (1990) call for organizations to shift their process management toward the inter-functional and inter-organizational levels. On the **inter-functional level**, organizations focus on processes that are executed within the organization but cut across multiple functional departments. In addition, on the **inter-organizational level** as the highest level of abstraction, organization consider their end-to-end processes, that are, ‘‘*processes that interface with customers and suppliers of the organization*’’ (Dumas et al., 2013, p. 49) and thus, unfold across the focal organization and, potentially, additional organizations.

Figure 2. Conceptual elements of a business process (based on Schwickert and Fischer (1996, p. 6))

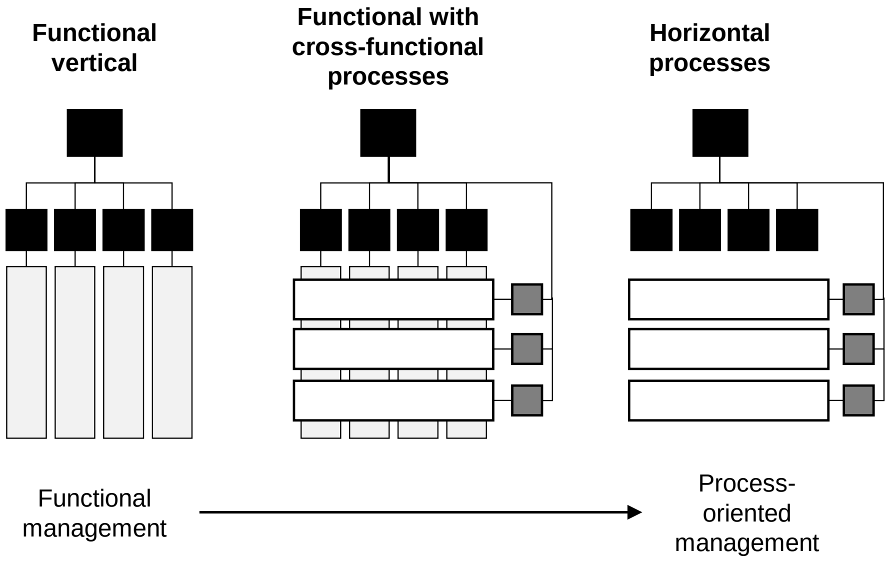


2.1.2 Process Orientation

By shifting their perspective on and management of processes toward end-to-end processes, organizations can facilitate **process orientation**. Process orientation refers to the organizational shift from a vertical, functional-oriented organization to a horizontal, process-oriented one (Gaitanides, 2012; Krcmar, 2015). To this end, the organization is structured along its end-to-end processes that define its value creation and are directed toward the respective customer, which can be a supplier, partner, client, or internal role (Kohlbacher, 2010). Consequently, process-oriented organizations focus on the outcomes of a process expected by internal or external customers and integrate all necessary activities to achieve the outcome into one process that is accounted for and operated by one department (Khosravi, 2016).

Nevertheless, process orientation is not a binary concept but a continuum, with organizations falling on the more or less process-oriented part of the spectrum (Kohlbacher, 2010). Accordingly, achieving process orientation is a long-term organizational transformation that involves a continuum of states. Three of the most commonly referred to states on the continuum from not process-oriented to process-oriented are displayed in Figure 3. In the **functional vertical** state, organizations focus on and manage processes within functional departments (Paim et al., 2008). In contrast, when organizations are structured functionally but prioritize management based on inter-functional processes, for example, from demand to delivery, they are in a **functional state with cross-functional processes** (Aparecida da Silva et al., 2012; Paim et al., 2008). Last, when organizations manage integrated, cross-functional processes in their entirety, which are directed to products, customers, and markets, they are in a state of **horizontal processes** (Paim et al., 2008).

Figure 3. Continuum of organizational process orientation (based on Aparecida da Silva et al. (2012, p. 765) and Paim et al. (2008, p. 709))



Process orientation is associated with several **benefits** as it allows organizations to optimize their increasingly interrelated, collaborative, and flexible processes (Dumas et al., 2013; Eggers, Hein, Böhm, et al., 2021). Process orientation has been associated with positive impacts on financial performance, product quality, customer satisfaction, delivery speed, and reliability (Kohlbacher, 2010), as it enables organizations to increase efficiency while focusing on the customer's needs and producing outcomes to meet those needs (Christiansson & Rentzhog, 2019). For example, organizations can reduce unnecessary, even detrimental, process variations and complexity and instead implement value-adding, streamlined processes that increase the speed of complaint handling, delivery reliability, and customer satisfaction (van Assen, 2018). This also provides employees with a broader notion of the organization's goals and can help them focus their actions on achieving goals for their functional departments, the organization, and their customers (Corallo et al., 2010).

However, transforming into a process-oriented organization bears several **challenges**. In particular, a lack of management support to initiate and drive the transformation and establish a process-oriented culture is considered one of the primary reasons why the transformation toward process orientation fails (Van Looy & Devos, 2019). In addition, organizations require transparency in their business processes to develop a shared understanding of the current process landscape and measure process performance, enabling them to develop a vision and roadmap for process transformation (Vlahovic et al., 2010). This also includes fostering process awareness in the workforce so that "*every employee is aware of the customer, and understands that, regardless of his or her job function, he or she is a part of a value chain creating value for customers*" (van Assen, 2018, p. 447). Furthermore, research indicates that clear responsibilities, for example, through the assignment of process owners, are fundamental to aligning roles with the goals and structure of the process-oriented organization (Christiansson

& Rentzhog, 2019). Last, implementing a fully process-oriented structure is difficult in practice since research shows that functional and product knowledge remains important. As such, organizations are challenged to allow horizontal and vertical management to co-exist and coordinate their efforts (Corallo et al., 2010).

2.2 Business Process Management and the Transformation of Business Processes

2.2.1 Business Process Management

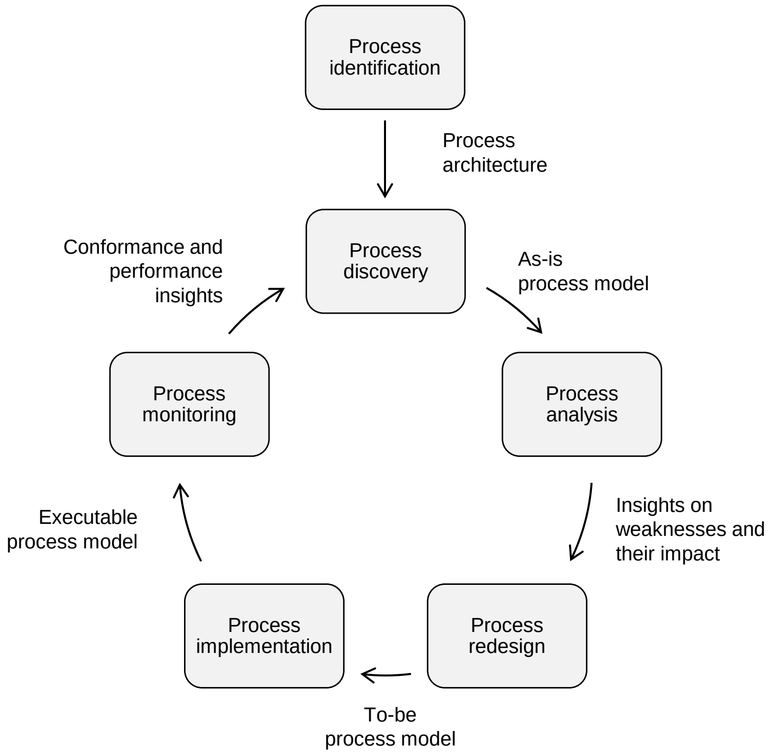
Evolving toward process orientation requires organizations to engage in BPM to continuously manage and transform their business processes. BPM can be considered "*a body of principles, methods, and tools to discover, analyze, redesign, implement, and monitor business processes*" (Dumas et al., 2013, p. 28). The roots of BPM can be traced back to the 1980s and 1990s when the ideas of Hammer (1990), Hammer and Champy (1993), and Davenport and Short (1990) to control, measure, and reengineer business processes for improving organizational performance gained traction. Summarized under the term **business process reengineering (BPR)**, scholars and practitioners alike employed „*the fundamental rethinking and radical redesign of business processes to achieve dramatic improvements in critical, contemporary measures of performance, such as cost, quality, service, and speed*" (Hammer & Champy, 1993, p. 35). But while the popularity of BPR rose for several years, it soon faded due to severe complications in practical use (Dumas et al., 2013). Especially the radical nature of process redesign was not suitable for every business process improvement initiative, and the technological support of business processes was not yet mature enough to provide the required flexibility (Dumas et al., 2013). Informed by the strengths and weaknesses of the BPR approach as well as related approaches, such as Total Quality Management or Six Sigma, and enabled by technological advances, scholars conceptualized BPM as a novel, overarching strategy to not only radically redesign but also to continuously monitor and (incrementally) transform business processes (Dumas et al., 2013; Grover & Markus, 2008). In the context of contemporary business process transformation, organizations need to particularly account for the increasingly important role of IT and, thus, ensure the alignment between their process needs and goals and their IT capabilities (Müller et al., 2017).

In the tradition of BPM, the orientation toward and management of business processes in organizations unfolds over the **enterprise**, **process**, and **implementation** levels and is driven by the centralized definition and adoption of a BPM strategy (vom Brocke & Roseman, 2015, p. 68). To this end, process management on the **enterprise level** focuses on establishing a vision, strategy, business process architecture, governance mechanisms, and process measurement systems to guide the organization's BPM practices (vom Brocke & Roseman, 2015, p. 55). Thus, BPM on the enterprise level is usually driven by the organization's top management, such as a Chief Process Officer (Dumas et al., 2013, pp. 24-25). As a result, the organization defines, for example, core, management, and support processes along with measures to evaluate process performance (vom Brocke & Roseman, 2015, p. 60). Then, guided by the BPM strategy defined on the enterprise level, BPM on the **process level** focuses on implementing the strategy by creating, redesigning, or improving specific processes through selected methods and tools, such as process modeling (vom Brocke & Roseman, 2015, p. 70). These change initiatives are often driven by process owners or BPM teams who oversee the efficient and effective operation of specific processes (Dumas et al., 2013, pp. 25-26). Last, on the **implementation level**, changes defined on the process level are implemented in the organization's systems and procedures, for example, supported by BPMS or WfMS (vom Brocke & Roseman, 2015, pp. 74-75). While the necessary technical changes are usually implemented by system engineers, the adherence to and execution of changed processes falls to the process participants (Dumas et al., 2013, pp. 25-26).

2.2.2 Business Process Management Lifecycle

While BPM encompasses various tools and techniques, the underlying activities can be outlined in the BPM lifecycle (Dumas et al., 2013; van der Aalst, 2016), which is illustrated in Figure 4.

Figure 4. Business process management lifecycle (based on Dumas et al. (2013, p. 21))



The **process identification** phase lays the foundation for the BPM lifecycle by producing a process architecture delineating the organization's processes and their interrelations as well as selecting performance measures to measure and analyze the processes. Based on the process architecture, the organization chooses processes of specific interest to transform through BPM (Dumas et al., 2013).

Next, during the **process discovery** phase, the identified processes are documented in their current state in the form of as-is process models (Dumas et al., 2013; van der Aalst, 2016).

Subsequently, in the **process analysis** phase, drawing on the as-is process models, issues in the processes are identified, measured, and documented, and the effort to improve upon the identified problems is estimated (Dumas et al., 2013).

Then, in the **process redesign** phase, the organization develops and evaluates change measures to address the identified challenges in the process. The most promising measures are selected and incorporated into a to-be process model that outlines the structure of the transformed process (Dumas et al., 2013).

Next, in the **process implementation** phase, the necessary changes to transform the process from its as-is state to the desired to-be state are prepared and executed. While these change measures also include organizational changes related to roles and responsibilities of the workforce, research shows that the development and deployment of IT systems to enable, support, or automate the new process design is of fundamental importance (Dumas et al., 2013).

Last, in the **process monitoring** phase, by collecting and analyzing data, the performance of the new process is evaluated, and shortcomings or deviations are identified and corrected (Dumas et al., 2013). Driven by organizations' dynamic nature and environmental conditions, the BPM lifecycle is continuously repeated to leverage improvement potentials and respond to changes by reevaluating and adapting processes (Christiansson & Rentzhog, 2019).

2.2.3 Process Awareness and Process Redesign

Literature on BPM reveals that the BPM lifecycle yields, in particular, two important outcomes for process transformation: **process awareness** and **process redesign**.

First, **process awareness** in the organizational context refers to employees’ awareness of how they perform their processes, how their actions are related to the end-to-end process, and how the outcomes of their actions impact internal and external stakeholders (Leyer et al., 2018). Consequently, process awareness is considered the foundation for process transformation since only if the organization and its workforce are aware of their as-is processes will they be able to acknowledge improvement potentials and define process redesign (Kohlbacher, 2010). Within the BPM lifecycle, process awareness is usually created throughout the process identification and process analysis phases when the as-is process landscape is documented and evaluated (Dumas et al., 2013).

However, research has shown that achieving process awareness is challenging. On the one hand, organizations struggle to create the necessary transparency on their processes that serves as the basis for process awareness (Christiansson & Rentzhog, 2019; Corallo et al., 2010; Kohlbacher & Gruenwald, 2011). In particular, identifying and reporting accurately on processes proves complicated in the organizational context because processes and activities often are not named, their quantity is unknown, process variability and complexity are undocumented, and process boundaries are not explicitly defined, thus blurring the lines between responsibilities or tasks (Corallo et al., 2010; Kohlbacher & Gruenwald, 2011). In consequence, the organization’s process knowledge is highly fragmented and difficult to access (Dumas et al., 2013; Malinova & Mendling, 2018). On the other hand, accessing and leveraging the organization’s process knowledge to achieve process awareness requires the organizational members to develop a shared process understanding (Christiansson & Rentzhog, 2019). However, to develop a shared process understanding, employees need to establish a shared language to discuss processes with their peers, which allows them to expand on their own limited experience and perspective on the process (Dumas et al., 2013; McCormack & Rauseo, 2005).

Second, **process redesign** refers to any minor or major change in a business process or the design of a new business process to improve existing or develop new innovative process designs (Dumas et al., 2013; Krcmar, 2015). Within the BPM lifecycle, measures for process redesign are developed in the redesign phase and implemented throughout the implementation phase (Dumas et al., 2013). Depending on the goal(s), the organizational redesign of processes can manifest in one or several dimensions of change. First, the organization can redesign a process to improve contact with **stakeholders**, for example, by bundling customer contacts and, thus, reducing the necessary number of contact points (Reijers & Mansar, 2005). Second, the organization can redesign the **implementation of the process**, that is, how the process is realized, for example, by eliminating unnecessary activities for processing orders (Dumas et al., 2013; Reijers & Mansar, 2005). Third, the organization can redesign the **behavior of the process**, that is, the way the process is executed, for example, by parallelizing or rearranging steps in a process (Dumas et al., 2013; Reijers & Mansar, 2005). Fourth, the organization can redesign the **organization of the process**, that is, the organizational structure and participants related to it, for example, by involving specific departments or resources in a process (Dumas et al., 2013). Fifth, the organization can redesign the **information** created or used by the process, for example, by validating information before it is sent out (Reijers & Mansar, 2005). Sixth, the organization can redesign how the process employs **technology**, for example, by implementing automation technology (Reijers & Mansar, 2005). Seventh, the organization can redesign the **external environment** the process is situated in, for example, by specifying interfaces with customers and partners (Reijers & Mansar, 2005). As a result of implementing process redesign, organizations can realize benefits in terms of time, for example, by decreasing the time required to process an order, cost, for example, by decreasing the cost associated to executing process steps, quality, for example, by improving the quality of a service delivered, and flexibility, for example, by improving the organization's capability to react to changes (Reijers & Mansar, 2005).

However, the rich tradition of research on business process redesign points toward several **social and technical challenges** organizations face when planning and implementing process redesign. First, the organization's leadership must actively participate in and commit to the redesign, clearly communicate its vision and purpose, and allocate the necessary time and resources to implement the redesign (Sarker & Lee, 2008). Conversely, the management's failure to engage in and communicate the process redesign initiative is considered a barrier to redesign success (Attaran, 2000). In addition, the organization must prepare the workforce to engage with the process redesign, for example, by providing employees with training to fulfill new roles or tasks or to work with new process technologies (Attaran, 2000) while establishing how the new roles and tasks unfold (Christiansson & Rentzhog, 2019). Still, the workforce might resist complying with the changes and adopting the process redesign due to insecurity and intransparency (Attaran, 2000). Last, successfully implementing process redesign requires a tight coupling with redesigning the underlying IT infrastructure to enable process change (Sarker & Lee, 2008). To this end, IT provides organizations with the capabilities to capture, access, and store information that serves as in- or output of processes, to process and manipulate information in the context of processes, and to support communication within and across processes (Sidorova et al., 2015). However, an inadequate understanding of the capabilities and limitations of the organization's process-enabling IT infrastructure can have detrimental effects on implementing process redesign, for example, due to unrealistic process designs or underspecified IT systems (Sarker & Lee, 2008).

2.3 Business Process Technology

2.3.1 Business Process Management in the Context of Digital Transformation

The continuous transformation of business processes enabled by BPM techniques is still of continued importance today (Dumas et al., 2013; Hammer, 2015). In particular, the dynamic and changing nature of contemporary industries requires organizations to sense the need for change and adapt their processes to ensure reliable operations and remain competitive (Hammer, 2015). In addition, new technological developments driven by digital transformation offer opportunities for organizations to optimize their processes but concurrently challenge them to react to ongoing technology-driven change and uncertainty (Baiyere et al., 2020; Mendling et al., 2020). Consequently, BPM is considered a critical technique for organizations to manage and transform their processes in the context of digital transformation (Kerpedzhiev et al., 2021; Mendling et al., 2020).

However, at the same time, digital transformation challenges many of the long-held assumptions that underlie BPM in traditional contexts (vom Brocke et al., 2016). First, scholars have assumed that BPM unfolds in a relatively stable organizational context in which processes are designed as a fixed solution to solve an organizational problem (Baiyere et al., 2020; Mendling et al., 2020). Yet, practice shows that the digital transformation of organizations can lead to fast and frequent context changes, for example, as new digital offerings and digital marketplaces fundamentally transform processes in industries (Böttcher et al., 2021), which require organizations to adapt and innovate their processes situationally (Mendling et al., 2020). Second, based on the understanding of processes unfolding in a stable context, BPM has traditionally focused on a reactive and problem-driven approach to monitoring and improving processes (Ahmad & van Looy, 2020; Kerpedzhiev et al., 2021). However, as digital transformation changes the environment in which organizations are embedded, they must create innovative process designs to meet changing stakeholder demands (Stjepić et al., 2020). Third, traditionally, BPM was guided by the assumption of IT systems fulfilling a supporting role for business process design and implementation, for example, in the form of WfMS or business process modeling tools (Sidorova et al., 2015). In contrast, recent technological advancements not only support business processes but enable new process designs that were previously considered infeasible. For example, nowadays, DLT allows for inter-organizational processes (Mendling et al., 2020).

Even though digital transformation is unfolding as a novel context for BPM, research has yet to explore its ramifications for BPM (Baiyere et al., 2020). Only recently, the first studies began to explore BPM under the paradigm of digital transformation and point toward important implications. For example, research shows that business processes and IT infrastructures become more flexible and modifiable to enable change in dynamic situations (Baiyere et al., 2020), which requires organizations to balance standardized processes and positive deviance to allow for process transformation to naturally emerge (Mendling et al., 2020). In line with this development, scholars indicate the need for future BPM practices to not only monitor and align standardized business processes but also to handle unpredictable, fragmented, and knowledge-intensive processes (Kerpedzhiev et al., 2021). In addition, research shows that novel digital technologies, such as BDA, present organizations with the opportunity to create insights into their operations, which opens up uncharted territory for incremental and radical process transformation (Kirchmer, 2021; Mikalef & Krogstie, 2020). Similarly, scholars point toward the potential of combining traditional BPM practices with novel automating business process technology, such as RPA, to achieve efficient but mature process automation (Flechsig et al., 2019). However, these studies are but the beginning of unraveling the opportunities and challenges that novel digital technologies entail for transforming business processes (Mendling et al., 2020; Wamba, 2017).

2.3.2 Diagnostic and Automating Business Process Technology

Informed by digital transformation, novel digital technologies have emerged to facilitate the management and transformation of business processes (Sidorova et al., 2015). These digital technologies relate to business process technology which comprises "*tools to analyze, document, specify, monitor, simulate, support and implement business processes*" (Draheim, 2010, p. 4). Research on business process technology has traditionally focused on technologies that support BPM, such as WfMS, business process modeling tools, and BPM suites (Sidorova et al., 2015). However, in recent years, novel technologies have entered research and practice that offer unparalleled opportunities for BPM and the digital transformation of business processes (Mendling et al., 2020). In particular, we observe two developments in business process technology that offer new capabilities for diagnosing and automating business processes.

The first development relates to the **vast and unprecedented amounts of process data** originating from IT systems inside and outside organizational boundaries that organizations nowadays can access (Abbasi et al., 2016; van der Aalst, 2016). This development grounds in the inextricable interrelation between business and IT today, which results in almost all business processes building on IT systems that support and track the activities of users with different goals, experiences, and habits. As a result, these organizational IT systems store rich process data (Kirchmer, 2021; van der Aalst, 2016). Accessing and analyzing these process data enables organizations to generate process knowledge that illuminates processes inside and outside the organization and fosters IT-enabled process change (Jurisch, 2014; Mikalef & Krogstie, 2020). Accordingly, there has been a significant increase in the use of **diagnostic business process technologies** in recent years, with process mining being one of the most prominent examples (Choudhary et al., 2021). Process mining is a data analytics technology that analyzes large amounts of event data readily available in today's IT systems to discover, monitor, and improve business processes (Baader & Krcmar, 2018; van der Aalst, 2016). As a result, organizations increasingly turn to process mining to create continuous transparency of their end-to-end business processes, serving as the foundation for process management and improvements (Grisold et al., 2020).

The second development relates to the **emergence of new development paradigms**, such as low code development (Bock & Frank, 2021) and new implementation approaches, such as DLT for decentralized data storage (El Ioini & Pahl, 2018), enabling organizations to achieve fast and scalable automation of business processes that was previously not feasible. Based on these developments, new **automating business process technologies** have emerged, such as RPA. RPA has gained attention from organizations across industries as a digital technology for automating tedious, repetitive manual tasks in IT systems (Hofmann et al., 2020). RPA utilizes software bots that are programmed to process structured input data on the interface of existing IS at the speed of a machine, providing an "*infinitely scalable virtual human*" (Willcocks & Lacity, 2016). Because RPA is often based on a low code approach, not only professional developers but also employees without an IT background can implement process automation, providing scalability (Osmundsen et al., 2019).

However, even though these developments in diagnostic and automating business process technology provide opportunities for organizations to understand and improve their business processes, we still lack knowledge of the mechanisms that underlie their adopting, using, and benefitting from these technologies. Taking the example of process mining as diagnostic business process technology and the examples of RPA and DLT as automating business process technologies receiving great attention in research and practice, we outline in the following the current state of the literature on their technical foundations and organizational use which foreshadows several opportunities for future research.

2.3.3 Process Mining

Definition

Process mining is rooted in the idea of generating process models that reflect how business processes are executed in reality rather than designing process models that reflect theoretical considerations or personal experience (van der Aalst & Weijters, 2004). Since business processes are at the heart of organizational performance and value creation, researchers and practitioners alike have long debated how to shed light on organizations' business processes as they are executed in reality. To this end, Agrawal et al. (1998) first formulated the idea of automatically reconstructing process models drawing on logged event data that reflect past executions of the process.

Driven by this idea, since then, process mining has emerged as a BDA technology for organizations to discover, monitor, and improve their business processes by utilizing event data that originate from their IT systems (van der Aalst, 2016; van der Aalst et al., 2012). These **event data** can be considered as "*digital footprints*" that are logged in the databases of IT systems every time a transaction is executed in the system (van der Aalst, 2016)—from a user sending out an invoice to the system automatically generating a reminder for late payment. Process mining leverages these event data to reconstruct the processes as they happened in reality (van der Aalst, 2016). To this end, the event data must fulfill three minimal requirements.

First, the event data must be sequentially recorded in the underlying IT system such that they can be ordered, for example, by including timestamps when storing an event (van der Aalst, 2016). Second, each event must relate to an activity, a well-defined step of the corresponding process, for example, sending out an invoice (van der Aalst, 2016). Third, each event must relate to a case reflecting a process instance, for example, the customer's order related to the invoice (van der Aalst, 2016). In addition, further information can be connected to the event, such as the cost associated with the event or the user carrying out the activity (van der Aalst, 2016). Given the potential number of users, systems, and processes, organizations have a wealth of process data at their disposal. However, as the data can be distributed across systems and logged in varying formats, organizations can generate meaningful insights only by integrating and analyzing the event data with analytics technologies (van der Aalst et al., 2012)[4].

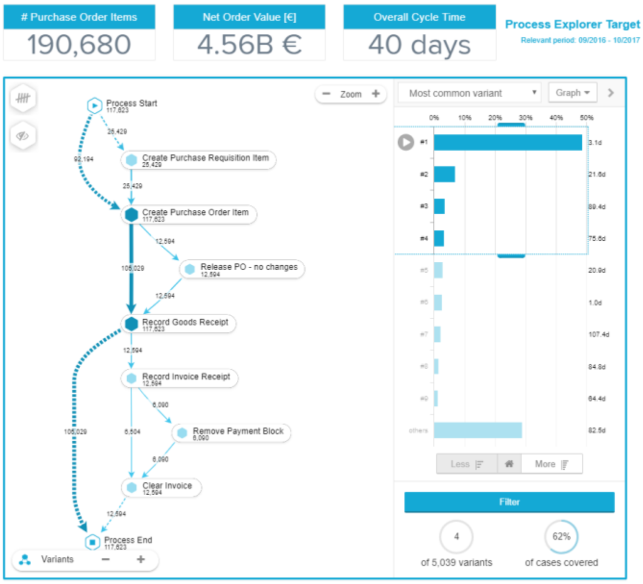
To this end, process mining leverages different **algorithms** to map the event data onto a process model—usually modeled as a Petri net—that represents the behavior discovered in the event data (van der Aalst, 2016). A Petri net is a bipartite graph that consists of places and transitions between the places as well as tokens that can flow through this network (van der Aalst, 2016). An example of a simple process mining discovery algorithm is the α-algorithm which scans the event log for particular patterns, such as reoccurring start and end activities, activities directly following one another, or activities never happening consecutively. Based on those patterns, the algorithm then gradually derives the connections of the final process model which can be modeled as a Petri net (van der Aalst, 2011).

Drawing on event data, process mining provides algorithmic support for three forms of process analysis: **process discovery**, **conformance checking**, and **enhancement** (van der Aalst, 2016). Through process discovery, organizations can automatically generate process models that reflect the underlying business process without prior process knowledge (van der Aalst et al., 2012). Using conformance checking, organizations can monitor processes for compliance with a pre-defined process model, which allows for detecting deviations and control for compliance with regulations (Pufahl & Rehse, 2021; van der Aalst, 2016). Lastly, process mining can enhance existing process models to reflect the actual process execution (van der Aalst et al., 2012). To support these analysis goals, contemporary process mining tools provide advanced visualization techniques (Rehse et al., 2023). An example of a visualization of a discovered purchase-to-pay process implemented in the Celonis[5] software is provided in Figure 5.

[4] It is to be noted that the processual reality of organizations is often more complex, leading to divergence and convergence in the event data (van der Aalst, 2019). For example, one event might be related to different cases (i.e., convergence) as different departments in an organization refer to and log the same process instance differently (for example, the sales department refers to a sales order, while the logistics department refers to a package). Similarly, for one case there might be multiple instances of the same activity (i.e., divergence) as the same activity is independently repeated multiple times (for example, multiple items in one customer order are each manufactured, picked, and packed) (van der Aalst, 2019). To deal with this complexity, in recent years, scholars have been debating novel algorithmic approaches, such as object-centric process mining, which to discuss in detail, however, goes beyond the scope of this dissertation. We would like to refer the interested reader to Adams and van der Aalst (2021); Adams and van der Aalst (2022); van der Aalst (2019).

[5] According to Gartner, the German company *Celonis* is currently among the leaders in the global process mining software market (Kerremans et al., 2023), which is one of the primary reasons we chose this software for implementing process mining. For the interested reader, more information is available at: https://www.celonis.com/

Figure 5. Exemplary process mining analysis for discovering a purchase-to-pay process (own screenshot from the Celonis process mining software)



Organizational Use of Process Mining

Since research on process mining emerged about two decades ago, scholars have primarily focused on evolving the technological basis, such as improving process discovery algorithms (Ailenei et al., 2011; Wang et al., 2012), event log generation (Tiwari et al., 2008), and process mining tools (Turner et al., 2012). In addition, studies focused on the technical implementation of process mining for specific industries and use cases, such as healthcare (Rojas et al., 2016), education (Ghazal et al., 2017), and supply chain management (Jokonowo et al., 2018). Acknowledging the fragmented literature on the implementation of process mining, Thiede et al. (2018) provide a literature review synthesizing empirical studies on process mining use for specific industry sectors and processes while focusing on prevailing data sources, process mining algorithms, and tools. Even though these studies provide valuable insights into the feasibility and implications of implementing process mining for specific use cases, they are restricted to the technical facets of process mining use by focusing on algorithms, tools, data sources, implementation strategies, and technical challenges.

In contrast, only recently has research expanded to include socio-technical questions of organizational adoption, implementation, and use of process mining (Badakhshan et al., 2022; Grisold et al., 2020; vom Brocke et al., 2021). Thus, when we first embarked on our journey of studying the organizational use of process mining, only little was known about the necessary **antecedents** for organizations to adopt and implement process mining. In particular, the research provided primarily anecdotal evidence from the study of singular use cases, such as the expertise for pre-processing of manually collected event logs (He et al., 2019), the collaboration between stakeholders (Alvarez et al., 2018) or the structured project management approach to implementing process mining (Mans et al., 2013). As a result, while research indicated the importance of socio-technical and organizational antecedents for successfully adopting process mining, there was a lack of a structured synthesis across use cases and industries.

Similarly, only a little attention has been paid to the **organizational use** of process mining, with most studies focusing on organizations using process mining to discover as-is processes (De Weerdt et al., 2012; Ho et al., 2009). Only recently, Badakhshan et al. (2022) provide the first study to take a broader perspective on the organizational use of process mining, thereby revealing three patterns of process mining use that prevail in practice. First, organizations leverage process mining for its data and connectivity features to collect and aggregate process data from various sources in- and outside the firm, which enables them to overcome challenges associated with traditional methods of process data collection (Badakhshan et al., 2022) that rely on subjective reports or incomplete observations (Dumas et al., 2013). Second, organizations use the process visualization features provided by process mining to discover and visualize end-to-end processes across IT systems and organizational boundaries to reveal process variations (Badakhshan et al., 2022). Third, organizations engage in process analytics provided by process mining to calculate process key performance indicators (KPIs), ensure process conformance, and develop process change measures (Badakhshan et al., 2022).

Last, **realizing value potentials** through the organizational use of process mining —beyond the generation of process models—had remained largely unaddressed when we first started our research project. Instead, studies reporting on process mining for organizational use cases only marginally and selectively pointed toward benefits, such as achieving increased transparency on anomalous process variations (Jans et al., 2014) or correlating process characteristics with customer satisfaction (Ho et al., 2009). Again, the study of Badakhshan et al. (2022) was recently among the first to relate process mining to business values and shed light on pathways of value creation. In particular, they reveal that process mining enables organizations to realize monetary values, such as optimization of working capital, non-monetary values, such as increased customer satisfaction, and process efficiency, such as reducing process cycle times (Badakhshan et al., 2022). Still, research on the organizational use of process mining is in its infancy, and we lack a deeper understanding of how organizations engage with process mining and profit from the unprecedented transparency of their processes (Grisold et al., 2020).

2.3.4 Robotic Process Automation

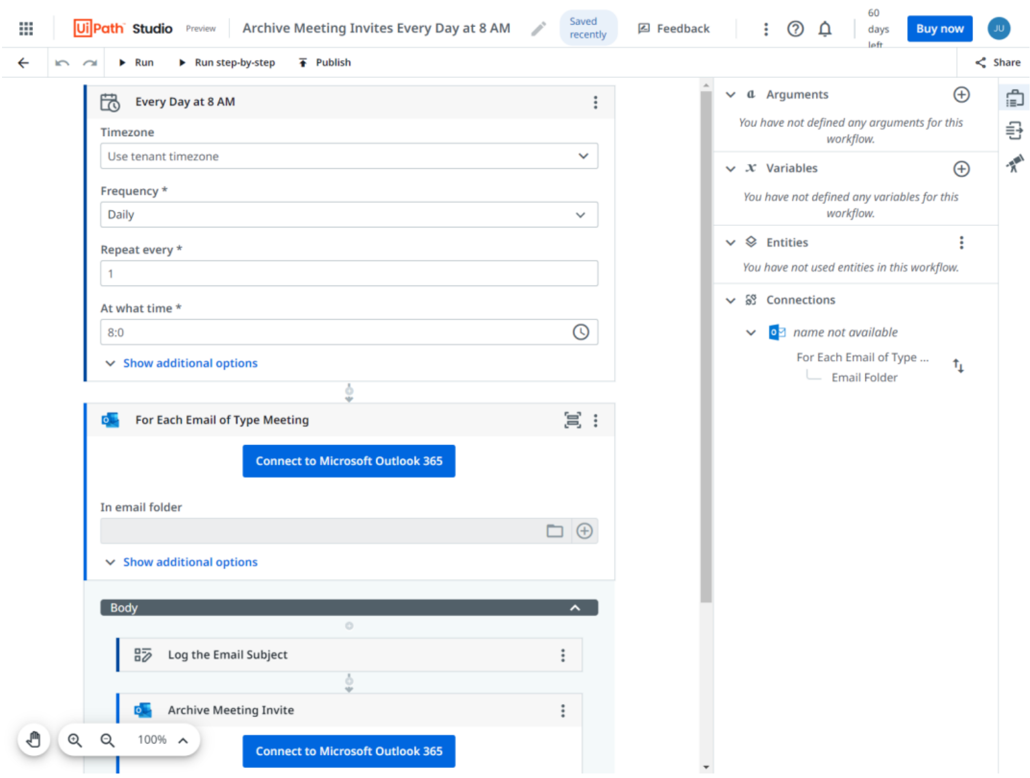
Definition

RPA emerged in recent years as a technology for automating processes through **software bots** that interact with IT systems through the user interface to imitate behavior that was formerly manually executed by human employees (Lacity & Willcocks, 2015; van der Aalst et al., 2018). As such, an RPA bot represents an "*infinitely scalable virtual human that can be instructed very quickly in order to carry out operational procedures at the speed of a machine*" (Willcocks & Lacity, 2016, p. 66). Since the bot depends on the structured specification of these procedures, processes that are particularly well-suited for automation with RPA are repetitive, rule-based, and occur in high volume (Hofmann et al., 2020). Such processes often unfold at the interface between two disconnected IT systems, such that an employee takes input from one system, processes it according to a set of rules, and enters the output into another system

(Willcocks & Lacity, 2016). Implementing RPA for these processes relieves employees of time-consuming, cumbersome tasks and helps them focus on more value-adding activities (Asatiani & Penttinen, 2016).

In contrast to traditional automation technologies, such as WfMS or backend automation, RPA does not require changes in the programming logic of underlying IT systems but runs on the user interface of these systems (Willcocks & Lacity, 2016). Accordingly, RPA is considered a **lightweight, low code automation technology** (Bock & Frank, 2021; Bygstad, 2017). To this end, employees can configure RPA bots on low code platforms that enable the "*rapid application development, deployment, execution and management [of bots] using declarative, high-level programming abstractions*" (Bock & Frank, 2021, p. 733). An example is the use of drag-and-drop features that automatically generate program code to create automated workflows (Bock & Frank, 2021; Willcocks & Lacity, 2016). An example of an RPA-automated process using the RPA software UiPath is illustrated in Figure 6. Consequently, the configuration of RPA bots does not require implementation skills or an IT background, which enables SMEs without technical knowledge, such as HR specialists or sales representatives, to develop RPA bots (Lacity & Willcocks, 2016b). These non-professional developers are considered citizen developers (Bock & Frank, 2021).

Figure 6. Exemplary configuration of an RPA bot for automating the archival of meeting invites in Outlook (own screenshot from the UiPath Studio software)



Organizational Use of Robotic Process Automation

As RPA only recently emerged as a new tool for lightweight process automation, research has just begun exploring socio-technical questions about its use in organizations (Syed, Suriadi, et al., 2020). In particular, studies primarily have yielded first insights into the technical and operational benefits of adopting RPA and the necessary capabilities for RPA implementation (Herm et al., 2020; Syed, Suriadi, et al., 2020).

First, studies point toward the **technical benefits** of RPA for realizing automation that is "*minimally invasive*" (Ratia et al., 2018) and easy to integrate into the existing IT infrastructure (Gao et al., 2019), which allows organizations to eliminate the costs for implementing changes in their underlying systems (Romao et al., 2019). In addition, RPA enables organizations to automate processes that were previously technically difficult to automate due to a lack of application programming interfaces (APIs) between IT systems that would allow for direct interaction (Lewicki et al., 2019; Wanner et al., 2019). Last, implementing and deploying RPA bots is less risky and complex than traditional backend automation as it allows for low code implementation and the reuse of components, facilitating the continuous development and adaptation of RPA bots (Maalla, 2019; Mager, 2019).

Second, RPA allows organizations to achieve **operational benefits** by automating repetitive and labor-intensive processes (Willcocks & Lacity, 2016). To this end, RPA allows the faster (Lacity & Willcocks, 2016a) and less error-prone automatic execution of processes (Jimenez-Ramirez et al., 2019), which frees employees of non-value adding activities and leads to operational cost savings (Mendling et al., 2018). In addition, these effects have been shown to increase employee satisfaction and reduce critical workload (Marek et al., 2019; Šimek & Šperka, 2019). Moreover, RPA contributes toward increased productivity and process effectiveness (Wanner et al., 2019) and triggers organizations to shed light on and standardize their processes (Mendling et al., 2018). Last, RPA provides organizations with a tool for scalable process automation as the implementation is no longer dependent on the capabilities of IT experts (Lacity & Willcocks, 2016b). Instead, citizen developers in the business departments use RPA to automate their processes, which research refers to as the decentralized approach to RPA implementation (Osmundsen et al., 2019). In contrast, organizations can also follow the centralized or the hybrid approach, in which the implementation is either executed or supported by a central CoE (Noppen et al., 2020; Osmundsen et al., 2019)—while, however, limiting the scalability of RPA implementation.

Third, research shows that organizations need to provide **capabilities to implement RPA** successfully (Herm et al., 2020; Syed, Suriadi, et al., 2020). On the one hand, organizations need to account for changes in processes and roles as RPA bots automatically execute activities and, thus, free employees to take on new tasks (Mendling et al., 2018). This also includes training for employees to raise awareness and build RPA skills to participate in implementing and using RPA bots (Balasundaram & Sirish, 2020; Naga Lakshmi et al., 2019). On the other hand, organizations need to evaluate the suitability of RPA for automating their processes, for example, regarding the attainment of organizational goals or the current state of their process landscape in terms of digitization and standardization (Herm et al., 2020; van der Aalst et al., 2018). Finally, organizations have to decide on how to govern the implementation of RPA, such as in a decentralized, centralized, or hybrid RPA development setting, while considering the different (dis-)advantages for the adoption and scaling of RPA (Herm et al., 2020; Syed, Suriadi, et al., 2020).

Although research has yielded valuable insights into the organizational use of RPA, scholars also point toward technical, managerial, and organizational questions regarding the successful adoption of RPA that remain unanswered. First, from a technical perspective, there is a lack of guidance on designing and implementing RPA bots (Ratia et al., 2018), for example, based on design patterns. Instead, RPA bot programming is primarily a manual effort driven by trial and error, which is tedious and fault-prone (Leno et al., 2018; Syed, Suriadi, et al., 2020) and can later complicate bot adaption and maintenance (Geyer-Klingeberg et al., 2018). Second, from a managerial perspective, it remains unclear how organizations can strategically manage and govern RPA implementation and use (Hofmann et al., 2020; Lacity & Willcocks, 2016a), particularly in a hybrid or decentralized setting that deviates from the traditional centralized IT development setting (Syed, Suriadi, et al., 2020). The decentralized setting poses particular challenges as citizen developers without an IT background engage in development activities which can lead to difficulties in taking on unfamiliar responsibilities (Lacity & Willcocks, 2016b; Syed, Suriadi, et al., 2020), such as RPA implementation and maintenance, and in balancing operational and development roles (Osmundsen et al., 2019). Third, from an organizational perspective, arises the question of how organizations can realize and measure benefits from using RPA (Naga Lakshmi et al., 2019; Plattfaut, 2019). When we started our research, there was no consensus on best practices for realizing organizational benefits from RPA (Syed, Suriadi, et al., 2020), and only sparse knowledge existed on how to measure the organizational impact of using RPA bots (Wanner et al., 2019).

2.3.5 Distributed Ledger Technology and Smart Contracts

Definition

The notion of DLT first received broad attention in research and practice in 2008, when a person (or group of people) by the pseudonym Satoshi Nakamoto published their whitepaper proposing Bitcoin as a cryptocurrency based on DLT (Khan et al., 2021; Nakamoto, 2008). Since then, the concept of DLT has also gained importance in enabling the automation of business processes (Nzuva, 2019), particularly through the implementation of smart contracts (Wang et al., 2019).

In 2008, Bitcoin was introduced as a peer-to-peer (P2P) system of electronic cash that circumvents the need for a trusted third party, such as a bank, to mediate financial transactions (Nakamoto, 2008). To this end, Bitcoin is based on the concept of DLT, a **distributed database** that records the transactions transpiring in a P2P network (Khan et al., 2021). In particular, the distributed database—or ledger—is maintained by the network of P2P nodes, for example, computers or other storage devices, that can be distributed geographically or institutionally so that each node has a copy of the ledger (Khan et al., 2021; Sunyaev, 2020). Thereby, DLT avoids developing any single point of failure (El Ioini & Pahl, 2018).

The fundamental idea of DLT is to facilitate the interaction of untrusted peers without needing a trusted third party to mediate the interaction (El Ioini & Pahl, 2018). To realize this scenario, DLT draws on two principles. First, DLT employs **cryptographic means** to ensure that data are stored immutably on the ledger so that data can only be appended to but not updated or deleted from the ledger (El Ioini & Pahl, 2018; Sunyaev, 2020). To this end, data immutability is achieved through functionalities such as digital signatures and fingerprints, for example, realized through hash functions and timestamps that provide data validity (Swan, 2015). Second, DLT builds on **consensus mechanisms** to ensure that the peers in the network agree on a consistent state of the distributed stored data (Sunyaev, 2020). Acknowledging these principles, various DLT implementations have emerged in practice, with the blockchain being arguably one of the most famous examples (Swan, 2015).

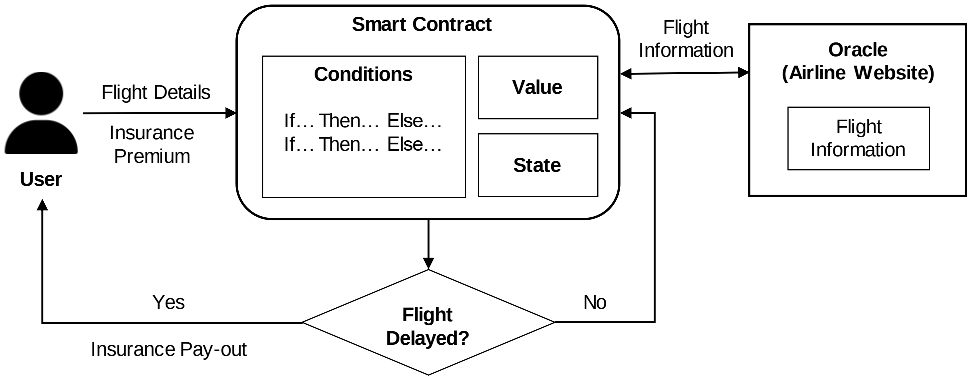
As an important instance of DLT, the blockchain enables the implementation of **smart contracts**, which serve as a promising means of process automation (Swan, 2015). Even though the concept of smart contracts was already proposed by Szabo (1996), its technical realization was not feasible at the time and only became attainable with the emergence of the blockchain more than a decade later (Cuccuru, 2017; Tapscott & Tapscott, 2016). Following the definition of Tapscott and Tapscott (2016, p. 101), smart contracts comprise "*computer programs that secure, enforce, and execute settlement of recorded agreements between people and organizations*." Metaphorically speaking, smart contracts resemble the concept of a vending machine where inserting money and selecting a product will always automatically lead to the same predetermined result (given that the machine is not broken) (Swan, 2015). Thus, from a technical perspective, smart contracts are programmed if-then-else conditions (Cuccuru, 2017). These programmed conditions reflect the parties' agreed-upon rules and ensure that these rules and corresponding operations are automatically executed when certain trigger conditions are met (Wang et al., 2019). The resulting code is then deployed in a decentralized, trusted, and shared way on the blockchain, which can be realized through platforms such as Ethereum or Hyperledger Fabric (Wang et al., 2019). Based on this code, smart contracts reflect either the digital version of an actual contractual agreement between different parties or a desired relationship without any contractual obligations or rights (Cuccuru, 2017). Therefore, no intermediaries are required to facilitate the transaction (Wang et al., 2019).

Organizational Use of Distributed Ledger Technology and Smart Contracts

The technological concept of smart contracts enables their application to various organizational use case scenarios, ranging from the trustworthy tracking of products in supply chains over improving and automating bureaucratic processes in e-government to combatting fraud in industries such as healthcare, food, and energy, to name but a few (Khan et al., 2021; Wang et al., 2019). To this end, recent literature reviews systematically synthesize our knowledge of smart contract applications and, thus, illustrate the manifold ways that smart contracts are being adopted in research and practice (see Khan et al. (2021); Nzuva (2019); Wang et al. (2019)).

From these studies emerges the notion of smart contracts as a promising technique for **organizational process automation**. In particular, smart contracts assure the automatic and transparent execution of agreed-upon rules, allowing manual labor and human judgment to be removed from the equation (Swan, 2015). We illustrate this automation potential by taking the example of flight delay insurance policies deployed and automatically managed through a smart contract on the blockchain (Gaggioli et al., 2019). To this end, the insurance policy terms are programmed in the smart contract's conditions. The user then selects a policy according to their needs, provides details on their planned flight, and pays the insurance premium to the smart contract. Once the insured flight lands, the smart contract automatically receives the flight information from the airline's website (these external information sources are referred to as *Oracles*). Based on the data it receives from the Oracle, for example, information on a flight delay, and its current state, the smart contract verifies if the predefined conditions are met and then automatically calculates and transfers the insurance pay-out to the user (Gaggioli et al., 2019; Wang et al., 2019). In this scenario, the smart contract eliminates the need for a trusted third party, such as an insurance firm, but instead functions as the insurance itself by automatically providing the user with the necessary processes. Figure 7 illustrates the exemplary process.

Figure 7. Exemplary smart contract for the case of flight delay insurance (based on Gaggioli et al. (2019, p. 5) and Wang et al. (2019, p. 2267))



Although smart contracts hold promise for automating processes, previous research has identified various **challenges** associated with the organizational implementation and use of the technology. First, for organizations to trust smart contracts, they need to have knowledge of their specific design. However, the technical nature of smart contract source code makes it difficult for non-experts to read and understand (Cuccuru, 2017). Second, transparency, a key property of DLT, raises concerns in organizations regarding privacy. For instance, financial transactions are often considered confidential, which could hinder the adoption of smart contracts for automating business processes (Kosba et al., 2016). Third, organizations need to ensure the reliability of external data sources accessed by smart contracts, possibly through the involvement of a trusted third party (Cuccuru, 2017). Finally, the immutability of smart contracts poses a challenge for organizations, particularly during the development and deployment phases, as errors cannot be easily corrected through software updates (Wang et al., 2019). Resulting from these complications, smart contracts are only slowly being adopted in practice (Clougherty Jones et al., 2019). Instead, organizations rely primarily on traditional process automation technologies, such as ERP systems or WfMS, to integrate business functions, control process execution, mirror process steps, and automatically execute specified process flows (Kumar et al., 2001; Lee & Lee, 2000). This raises the question if smart contracts offer a novel and valuable opportunity for process automation and how organizations can benefit from their implementation while addressing emerging challenges. However, research thus far lacks an adequate understanding of how the automation provided by smart contracts differs from that of well-established automation technologies (Cai et al., 2019) and how organizations can overcome complications when implementing smart contracts (Wang et al., 2019).

3 Research Strategy

In the following, we outline the research paradigm, including the underlying ontological and epistemological assumptions, and the qualitative research strategy, including the research methods, that this dissertation builds upon.

3.1 Research Paradigm

Any researcher is guided by their research paradigm, which reflects their interpretive framework consisting of a "*basic set of beliefs that guides action*" (Guba, 1990, p. 17) and defines how the world should be understood and studied (Denzin & Lincoln, 2011, p. 13). Hence, in choosing a research paradigm, the researcher makes foundational assumptions about what the nature of reality is (**ontology**), what can be known about reality (**epistemology**), and how to gain knowledge about reality (**methodology**) (Denzin & Lincoln, 2011, pp. 12-13). For the research conducted in this dissertation, we chose a **constructivist research paradigm** that consists of a relativist ontology, a subjectivist epistemology, and qualitative research methods (Lincoln et al., 2011). We considered this research paradigm well suited to our research objective of understanding how organizations adopt and implement novel business process technologies and their implications on BPM because it enables us to construct meaning from the lived experience of organizations to inform and improve practice (Lincoln et al., 2011, p. 106).

Constructivism adopts a **relativist ontology**, which assumes that multiple realities exist that depend on the people who hold them so that multiple interpretations can always result from any inquiry (Guba, 1990, pp. 26-27). Consequently, relativist ontology argues that there is not one singular reality but that reality is constructed intersubjectively through the experiences and interactions of individuals (Lincoln et al., 2011, pp. 102-103). For example, people's perception of an efficient business process will vary depending on the historical, industrial, cultural, and financial circumstances in which they and the organization are embedded. As a result, the researcher can never be separated from the reality they study. On the contrary, the researcher is fused with the inquired phenomenon as the process of inquiring about the phenomenon unfolds in the interaction between the researcher and the phenomenon (Lincoln et al., 2011, p. 103). In other words, the researcher generates findings and meaning through interacting with the people they study while being inevitably influenced by their own experiences, knowledge, and values (Lincoln et al., 2011, pp. 103-104).

Acknowledging this inextricable link between the researcher and the studied phenomenon, constructivism assumes a **subjectivist epistemology** (Guba, 1990, pp. 26-27). The subjectivist epistemology establishes that the researcher constructs their subjective understanding of reality driven by their experiences and interactions with the world, as do the individuals inquired in the research process (Lincoln et al., 2011, p. 103). Still, through interaction and collective reconstruction, individuals can coalesce around consensus and find intersubjective agreement (Lincoln et al., 2011, p. 108). As such, taking a subjectivist epistemological stance allows us to shed light on the socio-technical aspects of business process technology use in organizations that are shaped by the experiences and interactions of individuals in these organizations.

In sum, we chose a constructivist research paradigm to study the socio-technical adoption and implications of using novel business process technology in organizations because it enables us to inquire about the intersubjective, lived experiences of individuals in organizations using these technologies to reveal insights informing research and improving practice.

3.2 Qualitative Research Strategy and Research Methods

For the third and last component of our research paradigm, the methodology, we chose a hermeneutic approach based on a **qualitative research strategy**. Qualitative research is built on qualitative research methods, which rely on the interpretation and discovery of meaning in the qualitative material collected, for example, through observation or discussion with individuals (Denzin & Lincoln, 2018a, p. 43). In particular, drawing on qualitative research methods allows us to reveal and describe the characteristics, meanings, commonalities, and differences in people's actions and beliefs related to our phenomenon of inquiry (Erickson, 2018, p. 87), which is the adoption of business process technology in organizations and its implications for BPM. As such, qualitative research always precedes quantitative research in that it sheds light on the foundational characteristics of a phenomenon that can then be measured through quantitative research methods (Erickson, 2018, p. 87).

However, qualitative research approaches are subjected to criticism when applied in the natural sciences, which often follow a positivist or post-positivist approach that assumes the existence of one objective reality that can be (imperfectly) apprehended by quantitative methods (Lincoln et al., 2011, pp. 102-103). Hence, qualitative research is critiqued for not capturing the value-free "truth" that is assumed to be independent of personal experience and opinion (Denzin & Lincoln, 2018a, p. 40). Similar criticism is also evident in the IS discipline, with qualitative IS scholars reporting pressure to meet the supposed standards of natural science imposed on their research endeavors (Siponen & Klaavuniemi, 2021).

The debate about the diverging underlying research paradigms, particularly constructivist vs. (post-)positivist, fuels the dichotomy between qualitative vs. quantitative research and has been going on for decades (Denzin & Lincoln, 2018a, p. 32). However, in recent years voices have been raised questioning the clear divide between qualitative and quantitative research approaches and challenging the assumption that only quantitative methods are to be used legitimately in the natural sciences (Denzin & Lincoln, 2018a, p. 32). First, any data collection and analysis—qualitative and quantitative—is executed and, thus, influenced by the researcher and their subjective perception. Hence, it is dubitable that value-free, objective data and their interpretation can ever exist, even in the natural sciences (Siponen & Klaavuniemi, 2021). Second, the lines between disciplines and their methods increasingly blur (or become known to be blurred), as disciplines traditionally considered part of the natural sciences use qualitative methods and social sciences use quantitative methods (Denzin & Lincoln, 2018a, p. 32; Siponen & Klaavuniemi, 2021). For example, biology, as a prime example of natural sciences, employs methods of observation—a qualitative research method—while sociology now employs methods of biostatistics—a quantitative research method (Denzin & Lincoln, 2018a, p. 32; Siponen & Klaavuniemi, 2021). Thus, claiming only quantitative methods as legitimate methods of natural science is seen as increasingly problematic and contradictory to practical evidence (Siponen & Klaavuniemi, 2021). Instead, scholars now converge on the notion that also "*qualitative observations are natural science methods*" (Siponen & Klaavuniemi, 2021, p. 58), which underlines their fundamental importance in shedding light on phenomena that researchers can only reveal through systematic observation (Bratich, 2018, pp. 911-918). Following this line of argumentation, this dissertation in the field of natural sciences adopts a qualitative research strategy to shed light on the little-understood phenomenon of the organizational use of novel business process technology through systematic observations and interpretations.

Following our qualitative research strategy, we applied various qualitative methods to inquire about our phenomenon of interest. First, we employed structured literature reviews as the primary and supportive research method to systematically synthesize existing knowledge on business process technology (Leidner, 2018). Second, we used case studies—both single and multiple—as a primary and secondary research method to gain rich insights into the intersubjective, multi-level use of business process technology in organizations (Yin, 2014). Third, we applied design science research as the primary research method to create and evaluate innovative artifacts that serve organizations to solve problems in the context of business process technology (Hevner et al., 2004). Fourth, we followed the taxonomy design process (Nickerson et al., 2013) to develop a systematic and usable framework for assessing process mining use cases. Table 4 gives an overview of all research methods used in the publications embedded in this dissertation. While detailed descriptions of these methods are provided in the corresponding publications, we offer a short overview of all methods in the following.

Table 4. Overview of research methods applied in the embedded publications

#	Title	SLR	SCS	MCS	DSR	TD
P1	Turning Big Data into Value: A Literature Review on Business Value Realization from Process Mining	●				
P2	No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness	○		●		
P3	Process Automation on the Blockchain: An Exploratory Case Study on Smart Contracts	○		●		
P4	Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development	○	○		●	
P5	Assessing Process Mining Use Cases: A Taxonomy of Antecedents and Value Potentials of Process Mining	○	○		○	●
P6	Leveraging Big Data for M&A: Towards Designing Process Mining Analyses for Process Assessment in IT Due Diligence	○		○	●	

Legend:

● Primary method used in publication
○ Secondary method used in publication

SLR Structured Literature Review
SCS Single Case Study
MCS Multiple Case Study
DSR Design Science Research
TD Taxonomy Development

3.2.1 Structured Literature Review

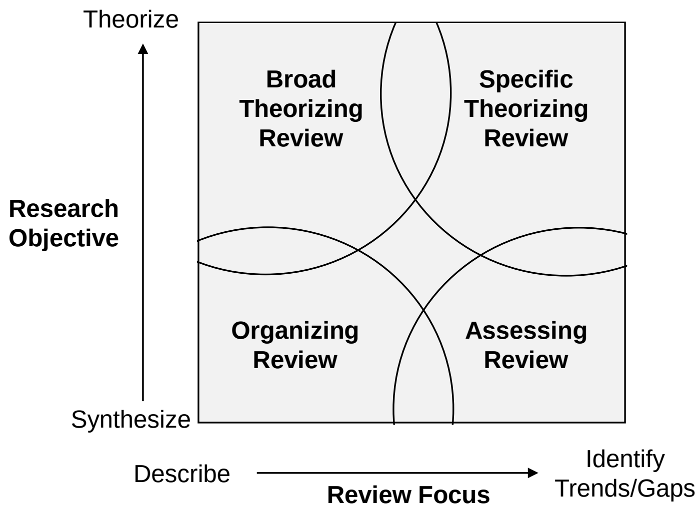
Particularly in a growing and dynamic research field such as IS, taking stock of the knowledge created is invaluable to advancing the discipline. Thus, literature reviews are an essential vehicle for advancing knowledge in the IS field by mapping previous efforts in the research field, synthesizing existing evidence, and providing the foundation for subsequent research (Paré et al., 2015). While scholars broadly pursue these goals by conducting a literature review, their specific intentions will vary depending on the type of literature review they choose to execute, in particular, as a secondary method to inform their study or as a primary, stand-alone method to develop theory (Okoli, 2015; Paré et al., 2015).

On the one hand, scholars conduct literature reviews as a secondary method within their research endeavor to inform their research question and provide a conceptual background (Paré et al., 2015). Such literature reviews are usually not exhaustive and focus on synthesizing the most important sources in a field to capture the current state of knowledge (Paré et al., 2015).

On the other hand, scholars conduct literature reviews as a primary, stand-alone method to provide a comprehensive synthesis of previous work to develop or inform theory (Leidner, 2018). The nature of these literature reviews can vary, for example, regarding their scope, goals, audience, and perspective (Cooper, 1988; Paré et al., 2015). Acknowledging this diversity of primary literature reviews, Leidner (2018) develops a polylithic framework that distinguishes four types of literature reviews depending on their research focus and research objectives, "*with research focus ranging from primarily description to the identification of gaps, and research objective ranging from primarily synthesizing to primarily theorizing*" (Leidner, 2018, p. 552). First, the **organizing review** focuses on describing the literature on a topic of interest with the goal of synthesizing knowledge, potentially guided by an emergent framework or existing theory to guide the process (Leidner, 2018). Second, the **broad theorizing review** strives to develop a theory, which can be a broad theory of an emergent topic or a new theory on an established topic, informed by the description of the literature on this topic (Leidner, 2018). Third, the **assessing review** aims to synthesize gaps or trends within a specific research stream, thus, taking a narrower focus than an organizing review. For an assessing review, the researcher takes existing theory as an a priori organizing device to code the literature and find areas that have been over- or understudied (Leidner, 2018). Fourth, the **specific theorizing review** focuses on theorizing about one particular gap identified in the literature and providing a theory informed by another literature stream to fill the gap (Leidner, 2018). Figure 8 illustrates the four types of literature reviews according to Leidner (2018).

Realizing the goal of any literature review requires the researcher to follow and document a structured and systematic approach that enables them to uncover and analyze all relevant sources (vom Brocke et al., 2009). To this end, IS literature provides various guidelines on organizing and executing structured literature reviews (Okoli, 2015; vom Brocke et al., 2009; Webster & Watson, 2002). One of the arguably most well-established guidelines for conducting a structured literature review was put forth by Webster and Watson (2002) and encompasses the following activities: First, the researcher needs to motivate and establish a clear goal for their literature review and define key concepts (Webster & Watson, 2002). Then, the researcher identifies the literature relevant to their topic by searching the field's leading journals and conferences as well as leading outlets from related research fields using defined keywords (Webster & Watson, 2002). Next, the researcher should go backward and forward by reviewing the citations in the identified articles as well as articles citing the identified articles (Webster & Watson, 2002). Last, the researcher analyzes the final set of articles in a concept-centric approach in order to synthesize recurring or outstanding themes evident in the literature (Webster & Watson, 2002). The analysis can be conducted by following specific coding procedures, such as grounded theory coding (Strauss & Corbin, 1994), which allows for the inductive discovery of concepts and their interrelations.

Figure 8. Polylithic framework of literature reviews (Leidner, 2018, p. 554)



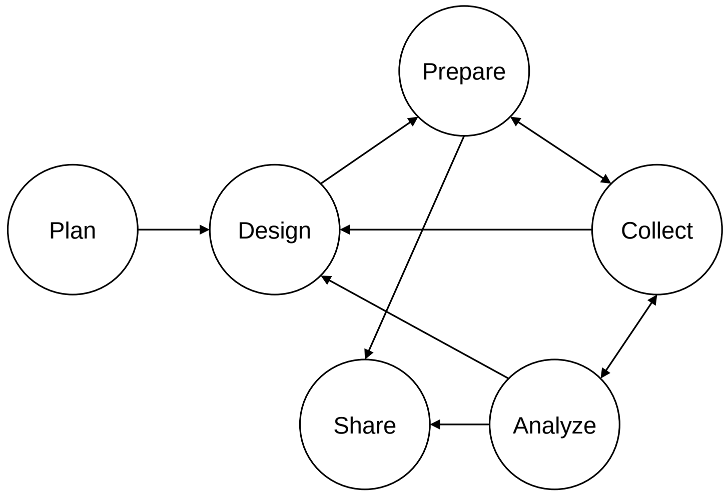
In the context of this dissertation, we conduct a structured literature review as a secondary method in publications **P2-P6** to provide a conceptual foundation, inform our respective research questions, and embed the publications within the literature on diagnostic or automating business process technology and BPM. In publication **P1**, we conduct a primary, stand-alone structured literature review following the approach of an assessing literature review as proposed by Leidner (2018). By choosing this type of literature review, we were able to synthesize current trends and gaps in the literature on organizational process mining use by analyzing the extant literature through the lens of IT artifacts within their immediate nomological net (Benbasat & Zmud, 2003).

3.2.2 Case Study Research

Case studies are a research strategy covering the logic of design, data collection, and data analysis to understand the dynamics present in a phenomenon (Eisenhardt, 1989; Yin, 2014, p. 14). In particular, a case study "*examines a phenomenon in its natural setting, employing multiple methods of data collection to gather information from one or a few entities (people, groups, or organizations). The boundaries of the phenomenon are not clearly evident at the outset of the research and no experimental control or manipulation is used*" (Benbasat et al., 1987, p. 370). Consequently, case studies are a suitable strategy for inquiring into "how" and "why" questions to illuminate phenomena and processes from the perspective of those involved (Pratt, 2009; Yin, 2014, p. 10)

For a long time, case study research lacked a clear approach and standardized activities for scholars to conduct and write about, which subjected case studies to the criticism of not being “enough” and short of contributions (Pratt, 2009). To this end, Yin (2014) defines a six-step linear but iterative process for conducting case study research (see Figure 9).

Figure 9. Case study research approach (Yin, 2014, p. 1)

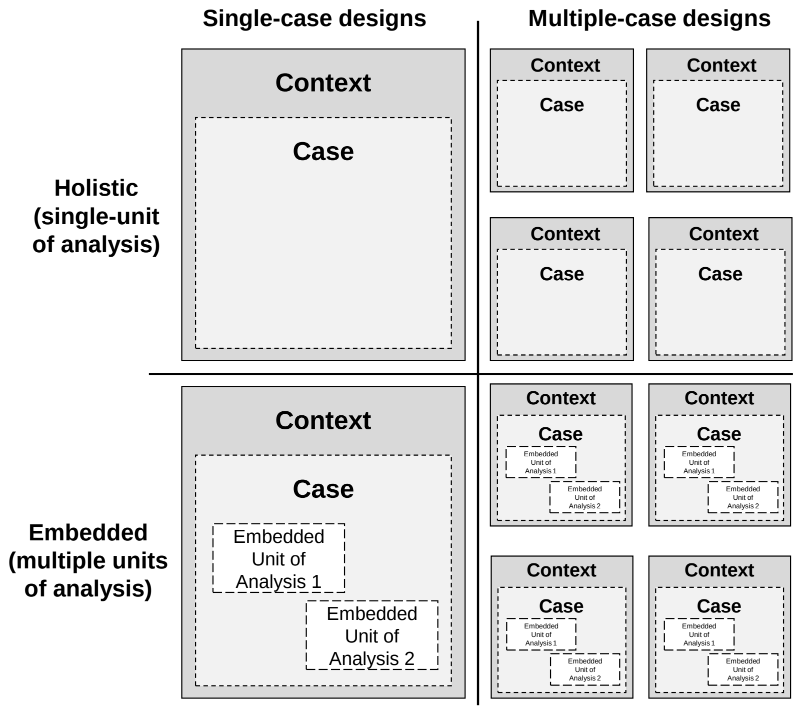


Case study research begins in the **planning phase**, in which the researcher defines their research question(s) and evaluates the appropriateness of employing a case study for investigating the research question(s) (Yin, 2014, pp. 10-11). In particular, case studies are suitable for studying contemporary events in their natural settings where no events or people need to be controlled or manipulated in the course of the research, and only little research and theory development on the phenomenon have been conducted thus far (Benbasat et al., 1987). Even though planning is important for the success of case studies, researchers need to be aware that the pre-defined research questions and concepts are only tentative and can shift throughout the process of generating insights from the case study (Eisenhardt, 1989).

In the **design phase**, the researcher develops the research design, which comprises the logical sequence of activities to proceed from the case study’s research question and covers the process from collecting data to drawing conclusions (Yin, 2014, p. 28). To this end, the researcher defines the case(s) and unit of analysis to be studied, potential initial propositions and the logic linking these propositions and the data, and criteria for interpreting the findings (Yin, 2014, p. 29). The case can take various forms, for example, an individual, organization, event, or other entity, and usually is chosen based on a theoretical sampling approach that defines criteria for selecting a case that makes the phenomenon “transparently observable” (Eisenhardt, 1989, p. 537). In addition, the researcher needs to decide whether to include one or multiple cases and whether to study one or multiple units of analysis within the case(s) (Yin, 2014, p. 50). On the one hand, a **single case study** allows for the in-depth study of a critical, unusual, common, revelatory, or longitudinal case (Yin, 2014, p. 55). The single case can encompass one unit of analysis (holistic single case study) when no logical subunits can be identified in the case, or the studied phenomenon requires a holistic approach. Alternatively, the case can also include multiple units of analysis (embedded single case study), such as multiple departments in the same organization, allowing for a more extensive analysis (Yin, 2014, p. 55). On the other hand, a **multiple case study** allows for the cross-case analysis of different cases that either predict similar (literal replication) or contrasting results (theoretical replication) for anticipatable reasons. In addition, each case may follow a holistic or embedded design depending on the research question (Yin, 2014, pp. 57-63). Figure 10 gives an overview of the four different case study designs. In addition to deciding on the case study design, the researcher might also state propositions and anticipate rival explanations for the phenomenon of interest that guide the data collection and analysis (Yin, 2014, pp. 30-36).

In the **preparation phase**, the researcher prepares the data collection by developing a case study protocol and screening candidate cases for the study (Yin, 2014, p. 71). The case study protocol encompasses an overview of the case study, the data collection procedures, data collection questions, and a guide for the case study report (Yin, 2014, pp. 85-86). Last, the researcher screens potential candidate cases for the study by collecting initial information and evaluating the cases according to defined selection criteria to decide on the final set of cases (Yin, 2014, p. 95).

Figure 10. Basic types of case study designs (Yin, 2014, p. 50)



In the **data collection phase**, the researcher gathers evidence from the cases to study the intended research question (Yin, 2014, pp. 103-104). In general, the data collection can rely on six sources: documentation, archival records, interviews, direct observation, participant-observation, and physical artifacts (Yin, 2014, p. 103). In particular, semi-structured expert interviews are among the most common qualitative data collection procedures used in the IS field (Myers & Newman, 2007). These interviews are based on guiding questions that comprise key areas of interest but also leave room for improvisation and unexpected insights (Myers & Newman, 2007). To increase reliability, any data collected should be documented and organized for later analysis in a case study database (Yin, 2014, pp. 123-127). In addition, the researcher should use multiple sources of evidence to triangulate the data, allowing converging lines of inquiry to emerge (Yin, 2014, pp. 123-127).

In the **data analysis phase**, the researcher examines and recombines the evidence to produce empirically based findings while ensuring internal and external validity (Yin, 2014, pp. 132-142). To this end, four general analysis strategies are available. First, the analysis can be guided by the theoretical propositions that led the case study (Yin, 2014, p. 136). Second, the analysis can work the data "from the ground up" so that concepts and their interrelations emerge inductively from the data (Yin, 2014, pp. 137-138). One commonly used inductive coding approach is grounded theory coding, which relies on the iterative open, axial, and selective coding of concepts emerging from the data (Gioia et al., 2013; Glaser & Strauss, 1967). Third, the analysis can organize the data according to some descriptive framework, such as topics relevant to the phenomenon (Yin, 2014, pp. 139-140). Fourth, the analysis can focus on defining and testing rival explanations for the studied phenomenon, which can also unfold in combination with the previous three strategies (Yin, 2014, p. 140).

Finally, in the **sharing phase**, the researcher shares the findings of the study in writing or orally with a defined audience (Yin, 2014, p. 176). Therefore, the researcher should include enough evidence to support their claims while letting the readers reach their own conclusions (Yin, 2014, p. 176). In addition, presenting evidence and emerging concepts in illustrations can improve the comprehensibility of the study (Gioia et al., 2013).

In the context of this dissertation, we conducted a single case study as a secondary research method in the embedded publications **P4** and **P5**. In **P4**, the single holistic case study of decentralized RPA implementation at a large automotive firm serves to shed light on the challenges and success factors of RPA implementation in this setting from a practical perspective and to evaluate the derived implementation framework. In **P5**, the single embedded case study enabled us to evaluate the derived taxonomy in the practical context of potential process mining use cases at a manufacturing firm. In addition, we conducted a multiple case study as a primary research method in the embedded publications **P2** and **P3** and as a secondary research method in **P6**. As a primary research method, the holistic multiple case study design allowed us to analyze and contrast multiple cases of process mining use in P2 and multiple cases of DLT use in P3. As a secondary research method, the embedded multiple case study design served to evaluate a framework for process mining use in the context of M&A by applying it to assess and compare multiple processes in different organizations.

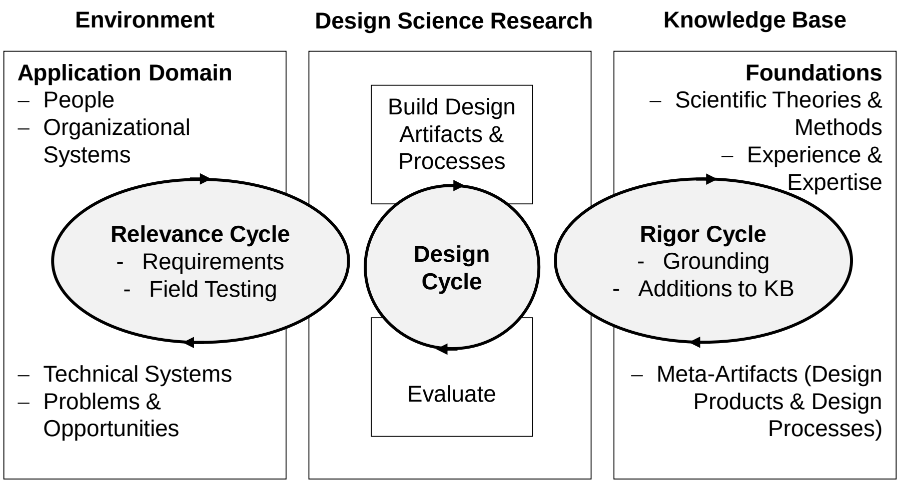
3.2.3 Design Science Research

One fundamental purpose of IS research is to produce scientific results that are beneficial to society and business (Hevner et al., 2004; Österle et al., 2011). Thus, design-oriented IS research is considered a pillar of IS research as it "*aims to develop and provide instructions for action (i.e., normative, practically applicable means-ends conclusions) that allow the design and operation of IS and innovative concepts within IS (instances)*" (Österle et al., 2011, p. 8). In particular, it focuses on the development of artifacts, "*namely constructs (e.g., concepts, terminologies, and languages), models, methods, and instantiations (i.e., concrete solutions implemented as prototypes or production systems)*" (Österle et al., 2011, pp. 8-9), that solve identified organizational problems (Hevner et al., 2004). In additionally to the development of artifacts, design science research is also expected to advance design knowledge, which can range from descriptions of the form and functions of the artifact to nascent design theory reflected in design principles to refined design theory (Baskerville et al., 2018; Gregor et al., 2020).

To inform this design-oriented research process and ensure the development of useful artifacts, Hevner (2007) proposes a three-cycle framework of design science research. In general, the framework consists of the relevance, rigor, and design cycles, which are iteratively traversed in the process of design science research and connect the contextual environment (relevance cycle) and the scientific knowledge base (rigor cycle) with the development of the artifact (design cycle) (Hevner, 2007). The three-cycle framework is illustrated in Figure 11.

First, the **relevance cycle** accounts for the purpose of design science research to address practical problems by embedding the design process within the application domain (Hevner, 2007). To this end, in the relevance cycle, the researcher inquires into the application domain, for example, an organizational problem, to identify requirements for the research and define acceptance criteria for the later evaluation of the developed artifact (Hevner, 2007).

Figure 11. Three-cycle framework of design science research (Hevner, 2007, p. 88)



Second, the **rigor cycle** focuses on incorporating the existing knowledge base to ensure a rigorous research process (Hevner, 2007). Thus, the researcher engages with the literature to synthesize the experiences and expertise defining the state-of-the-art in the application domain and to identify existing artifacts and processes in the application domain (Hevner, 2007). Consequently, by systematically identifying and applying suitable theories and methods from the knowledge base, the researcher ensures that the artifacts produced are research contributions to the knowledge base, not just practical implementations of IS artifacts (Hevner, 2007).

Third, the **design cycle** constitutes the heart of any design science research process as it draws on the insights from the relevance and rigor cycles to iteratively develop, evaluate, and refine the desired artifact (Hevner, 2007). The developed artifact can comprise an instantiation of the IS artifact as well as constructs, models, and methods applied in the process of developing and using it (Hevner et al., 2004). Additionally, the evaluation of the artifact plays a vital role in the design cycle to rigorously demonstrate its utility, quality, and efficacy (Hevner et al., 2004). Depending on the research context and the designed artifact, different evaluation techniques are available as illustrated by the taxonomy proposed by Prat et al. (2015), which encompasses the techniques demonstration, simulation- and metric-based benchmarking of artifacts, practice-based evaluation of effectiveness, simulation-and metric-based absolute evaluation of artifacts, practice-based evaluation of usefulness or ease of use, laboratory, student-based evaluation of usefulness, and algorithmic complexity analysis.

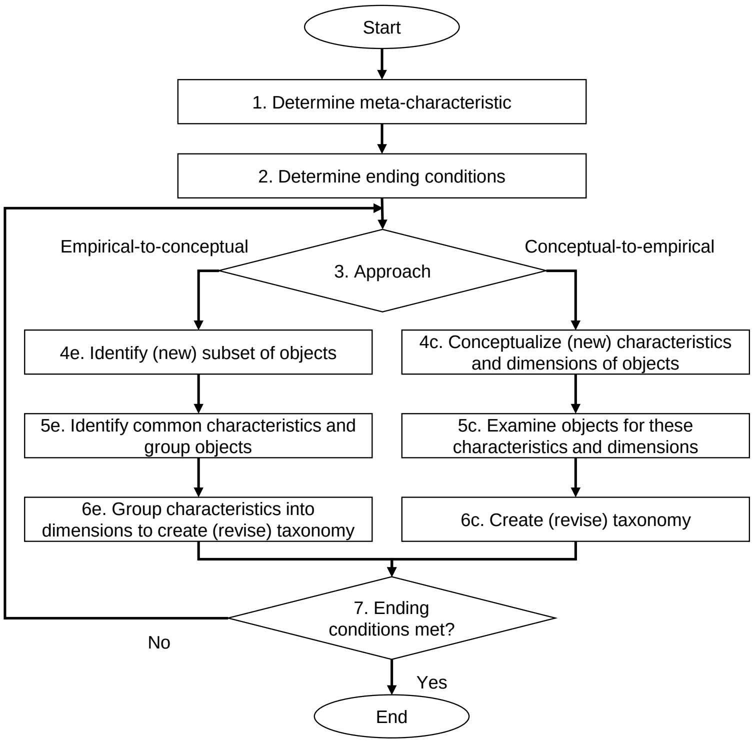
In this dissertation, we conducted a design science research approach as the primary research method in the embedded publications **P4** and **P6** and as a secondary research method in **P5**. In **P4**, following a design science approach, we developed a scientifically grounded and practically relevant software development framework that guides decentralized RPA development while supporting SMEs in their new roles and responsibilities as low code developers. In **P6**, we drew on a design science research approach to ensure practical relevance and scientific rigor while developing a novel, useful IT artifact based on process mining for supporting the process assessment in IT DD in the context of M&A transactions. In addition, we derived design knowledge to guide the artifact's construction by specifying design principles as the relationship between the problem and solution space (Gregor et al., 2020; Hevner et al., 2004). In **P5**, we followed a design science approach to develop a scientifically rigorous and practically relevant framework for assessing process mining use cases based on the taxonomy development method of Nickerson et al. (2013). To this end, the design science approach enabled us to ground the taxonomy development in extant research through the rigor cycle and to connect it to the real-world application domain through the relevance cycle while iteratively refining it in the design cycle by processing input from both cycles (Hevner et al., 2004).

3.2.4 Taxonomy Development

Taxonomies have emerged from the natural sciences, particularly biology, to categorize organisms (Nickerson et al., 2013). Still, they also have gained importance in other research fields, such as organizational and IS research, as a vehicle to organize knowledge in a field (Nickerson et al., 2013; Rich, 1992). In this context, a taxonomy is a classification of objects into separate groups that express the overall similarity between objects hierarchically (Rich, 1992). Consequently, a taxonomy enables the researcher to compare and contrast phenomena against one another, either as individual objects or as members of a larger division, and explore relationships between them (Nickerson et al., 2013; Rich, 1992).

To develop taxonomies, particularly for the application in IS research, Nickerson et al. (2013) propose a seven-step method (see Figure 12), which unfolds in iterative applications of empirical-to-conceptual and conceptual-to-empirical approaches. In the first step, the researcher identifies the **meta-characteristic**, which reflects the purpose and expected use of the taxonomy (Nickerson et al., 2013). In the second step, the researcher determines the **objective and subjective conditions that end** the taxonomy development process (Nickerson et al., 2013). The objective conditions specify that all objects have been examined; no objects were merged or split in the last iteration; at least one object is classified under each characteristic of each dimension; no new dimensions or characteristics were added in the last iteration; no dimensions or characteristics were merged or split in the last iteration; every dimension and every characteristic within a dimension is unique; each combination of characteristics is unique (Nickerson et al., 2013). In addition, the subjective conditions require the taxonomy to be concise, robust, comprehensive, extendible, and explanatory (Nickerson et al., 2013). In the third step, the researcher chooses the **approach** for the iteration, that is, either an empirical-to-conceptual or conceptual-to-empirical approach (Nickerson et al., 2013). On the one hand, in the **empirical-to-conceptual approach**, the researcher identifies objects they wish to classify and derives characteristics that discriminate between the objects. On the other hand, in the **conceptual-to-empirical approach**, the researcher first conceptualizes dimensions of the taxonomy without examining objects and then examines objects for the identified dimensions and characteristics (Nickerson et al., 2013). In the final step, the researcher **evaluates** whether the objective and subjective ending conditions are met and—in case they have not been fulfilled yet—re-iterates the process beginning with the third step (Nickerson et al., 2013).

Figure 12. Iterative taxonomy development method (Nickerson et al., 2013, p. 345)



In the context of this dissertation, we applied the iterative taxonomy development method as the primary research method in the embedded publication **P5**. In **P5**, we developed a systematic and usable framework for assessing process mining use cases based on antecedents and expected value potentials by following the taxonomy development method of Nickerson et al. (2013). The resulting taxonomy allows the organization of knowledge in the field of process mining antecedents and value potentials and the identification of relationships among the underlying concepts, such as assessing the cost-benefit ratio for process mining use cases (Nickerson et al., 2013). To ensure that the developed taxonomy is scientifically rigorous and practically relevant, we embedded the taxonomy development method within the three cycles of design science research (Hevner et al., 2004).

Part B

4 P1: Turning Big Data into Value: A Literature Review on Business Value Realization from Process Mining

Table 5. Fact Sheet Publication P1

Authors	**Eggers**, Julia[1] **Hein**, Andreas[1]
Author Affiliations	**1 -** Technical University of Munich, Garching, Germany
Outlet	**ECIS 2020** 28th European Conference on Information Systems, 2020, Virtual
Status	**Published**

Abstract. In recent years, process mining has emerged as the leading Big Data technology for business process analysis. By extracting knowledge from event logs readily available in information systems, process mining provides new ways to discover, monitor, and improve processes while being agnostic to the source system. Despite its undisputed practical relevance, we have a limited understanding of how organizations realize value potentials from applying process mining in different organizational contexts. Addressing this gap, we conduct an assessing literature review by analyzing 58 papers from the literature on process mining to synthesize the existing knowledge on business value realization from process mining. Our analysis is guided by adopting the perspective of process mining embedded within its organizational context. By analyzing the dimensions of the nomological net around process mining, we contribute to the broader research field of Big Data value realization twofold. First, we uncover which benefits organizations gain by applying process mining. Second, we analyze the organizational capabilities and practices that influence how organizations use and implement process mining. In addition, we reveal how process mining leads to business value realization. Based on these results, we suggest directions for future research on process mining in the organizational context.

5 P2: No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness

Table 6. Fact Sheet Publication P2

Authors	**Eggers**, Julia[1] **Hein**, Andreas[1] **Böhm,** Markus[1] **Krcmar**, Helmut[1]
Author Affiliations	**1** - Technical University of Munich, Garching, Germany
Outlet	**BISE** Business & Information Systems Engineering
Status	**Published**

Abstract. In recent years, process mining has emerged as the leading big data technology for business process analysis. By extracting knowledge from event logs in information systems, process mining provides unprecedented transparency of business processes while being independent of the source system. However, despite its practical relevance, there is still a limited understanding of how organizations act upon the pervasive transparency created by process mining and how they leverage it to benefit from increased process awareness. Addressing this gap, this study conducts a multiple case study to explore how four organizations achieved increased process awareness by using process mining. Drawing on data from 24 semi-structured interviews and archival sources, this study reveals seven socio-technical mechanisms based on process mining that enable organizations to create either standardized or shared awareness of subprocesses, end-to-end processes, and the firm's process landscape. Thereby, this study contributes to research on business process management by revealing how process mining facilitates mechanisms that serve as a new, data-driven way of creating process awareness. In addition, the findings indicate that these mechanisms are influenced by the governance approach chosen to conduct process mining, i.e., a top-down or bottom-up driven implementation approach. Last, this study also points to the importance of balancing the social complications of increased process transparency and awareness. These results serve as a valuable starting point for practitioners to reflect on measures to increase organizational process awareness through process mining.

6 P3: Process Automation on the Blockchain: An Exploratory Case Study on Smart Contracts

Table 7. Fact Sheet Publication P3

Authors	**Eggers**, Julia[1] **Hein**, Andreas[1] **Weking**, Jörg[1] **Böhm**, Markus[1] **Krcmar**, Helmut[1]
Author Affiliations	**1** - Technical University of Munich, Garching, Germany
Outlet	**HICSS 2021** 54th Hawaii International Conference on System Sciences, Virtual
Status	**Published**

Abstract. While business process automation through information technology has progressed over the last decades, smart contracts have recently emerged as a promising new means of automation. However, in practice, the adoption of smart contract-based automation is in its infancy, raising the question if the technology genuinely offers a unique approach to process automation. Drawing on an exploratory case study of four start-ups, we investigate the potentials for automation that organizations achieve through smart contracts and how smart contracts differ from established automation technologies, such as workflow management systems, enterprise resource planning systems, and robotic process automation. We contribute to the literature on process automation by unveiling transparent and immutable, cross-organizational, and decentralized automation as characteristics that differentiate smart contracts from established automation technologies. Besides, we provide practitioners with an understanding of application scenarios, potentials, and drawbacks of smart contracts for process automation.

7 P4: Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development

Table 8. Fact Sheet Publication P4

Authors	**Eggers**, Julia[1] **Wewerka**, Judith[2] **Viljoen**, Altus[1] **Krcmar**, Helmut[1]
Author Affiliations	**1** - Technical University of Munich, Garching, Germany **2** - Ulm University, Ulm, Germany
Outlet	**HICSS 2023** 56th Hawaii International Conference on System Sciences, Maui, USA
Status	**Published**

Abstract. Robotic Process Automation (RPA) has emerged as promising automation technology in recent years. Firms seize RPA for fast and cost-efficient low code process automation implemented and maintained decentrally in the business units by subject matter experts (SMEs) without IT development experience. However, decentralized RPA projects are reported to frequently fail and be prone to challenges as SMEs struggle to meet their new roles and responsibilities, such as developers or testers. Yet, research lacks an understanding of how challenges related to SMEs' roles and responsibilities unfold and how to address these challenges when executing decentralized RPA projects. To this end, our study employs a Design Science Research approach, drawing on literature and 14 expert interviews, to (1) systematically synthesize the challenges related to SMEs' roles and responsibilities and (2) derive a software development framework for supporting SMEs in their new roles and responsibilities in decentralized RPA projects. Thus, our study contributes to RPA and low code development research and provides SMEs with guidelines to navigate decentralized RPA projects in practice.

8 P5: Assessing Process Mining Use Cases: A Taxonomy of Antecedents and Value Potentials of Process Mining

Table 9. Fact Sheet Publication P5

Authors	**Eggers**, Julia[1] **Häge**, Marie-Christin[2] **Zimmermann**, Sina[1,3] **Gewald**, Heiko[3]
Author Affiliations	**1 -** Technical University of Munich, Garching, Germany **2 -** University of Mannheim, Mannheim, Germany **3 -** Neu-Ulm University of Applied Sciences, Neu-Ulm, Germany
Outlet	**AMCIS 2023** 29th Americas Conference on Information Systems, Panama City, Panama
Status	**Published**

Abstract. Process mining (PM) has gained traction as a Big Data Analytics technique to discover, monitor, and improve business processes based on event data that are available in organizations' information systems. However, despite high expectations and widespread use in practice, organizations still struggle to implement and realize value from PM. In particular, organizations, first, are challenged to identify and establish the antecedents necessary for implementing PM use cases, and second, lack guidance in identifying and assessing valuable PM use cases. Even though initial studies investigated socio-technical factors influencing the adoption, implementation, and value of PM on the organizational level, knowledge in the field is still fragmented, and we lack a systematic understanding of how organizations can assess antecedents for and value potentials of PM to identify valuable use cases. Thus, building on a design science research approach, we address this research gap by developing and evaluating a structured framework drawing on the taxonomy development method of Nickerson et al. (2013) for assessing PM use cases based on their antecedents and expected value potentials. We iteratively develop and evaluate the taxonomy grounded in theory by drawing on PM literature and related research fields and practice by conducting twelve semi-structured interviews at a German manufacturing corporation to apply and evaluate the taxonomy. Consequently, our study contributes to research on the organizational implementation and use of PM and enables researchers and practitioners to understand, operationalize, and assess the factors influencing the selection of PM use cases.

9 P6: Leveraging Big Data for M&A: Towards Designing Process Mining Analyses for Process Assessment in IT Due Diligence

Table 10. Fact Sheet Publication P6

Authors	**Eggers**, Julia[1] **Hein**, Andreas[1] **Böhm**, Markus[2] **Krcmar**, Helmut[1]
Author Affiliations	**1 -** Technical University of Munich, Garching, Germany **2 -** University of Applied Sciences Landshut, Landshut, Germany
Outlet	**PACIS 2023** 27th Pacific Asia Conference on Information Systems 2023, Nanchang, China
Status	**Published**

Abstract. The success of mergers & acquisitions (M&A) depends on the buyer's adequate due diligence (DD) assessment of the target firm. Assessing the target's IT-enabled processes recently emerged as a novel information technology DD (IT DD) responsibility. However, it remains unclear how to operationalize and conduct the process assessment in IT DD. To address this challenge, we propose the big data analytics technology process mining (PM) and follow a design science research approach, based on literature and 12 interviews, to reveal and operationalize requirements for process assessment in IT DD, demonstrate PM to measure the operationalized requirements, and derive design principles and enabling factors to guide the design, implementation, and use of PM for process assessment in IT DD. Consequently, our study contributes to research on IT DD, M&A, and PM and provides practitioners with design knowledge and a prototypical PM artifact to leverage PM for process assessment in IT DD.

Part C

10 Summary of Results

This dissertation builds on six embedded publications, which address the research questions of (1) unraveling the socio-technical antecedents for business process technology adoption, (2) demonstrating how the use of these technologies enables new approaches to BPM, and (3) revealing how, as a result, organizations can transform their business processes. Hence, in the remainder of this chapter, we provide a summary of the results for each of the three research questions.

RQ1: *What are socio-technical antecedents for the organizational adoption of novel business process technology?*

Organizational Capabilities and Practices as Socio-Technical Antecedents for the Adoption of Process Mining. Drawing on an assessing literature review (Leidner, 2018) and following a grounded theory coding procedure (Glaser & Strauss, 1967), in **P1** we contextualize process mining as an IT artifact within its nomological net leading to organizational adoption and use. Studying IT artifacts within their immediate nomological net allows IS researchers to unravel the socio-technical antecedents and procedures that enable organizations to adopt and benefit from IT (Benbasat & Zmud, 2003). Using the nomological net around process mining as a theoretical lens to analyze the findings of 58 empirical studies, we reveal organizational capabilities and practices as antecedents for process mining use and how these antecedents facilitate usage patterns of process mining and realization of business value.

To this end, we identify six organizational capabilities and five organizational practices that are fundamental for adopting and realizing value from process mining. First, organizations must establish organizational capabilities related to the organizational, data, and system context. The organizational context comprises project-related factors, such as support from the organization's **executive management**, the **availability of resources** to execute the project, and **expert knowledge** of data preparation and analysis implementation. In addition, the data and system context reflect process mining-related factors, such as the **availability** and **quality of raw process data** and **expertise** in the workforce to pre-process the data to produce concise event logs. Second, organizations need to provide organizational practices to foster the adoption of process mining, such as a structured **implementation procedure** and **project management**, a careful selection approach of **mining algorithms** and the focus of analysis, **collaborative practices** for project stakeholders and process owners, and **strategies** for interpreting and discussing results as well as for **communicating and visualizing** findings. In addition, we show how organizations, enabled by the socio-technical antecedents, can use process mining to discover, monitor, predict, and align their processes, allowing them to realize value potentials related to process efficiency, forecasting, conformance, standardization, and redesign.

Assessing Antecedents and Value Potentials of Process Mining for Use Case Selection. Enabled by the taxonomy development approach (Nickerson et al., 2013) embedded in a design science research strategy (Hevner et al., 2004), in **P5,** we iteratively develop and evaluate a framework for assessing process mining use cases based on required antecedents and expected value potentials. Driven by the observation that organizations still struggle to prepare for and select suitable process mining use cases, we engage with process mining and related literature and conduct interviews at a German manufacturing firm to synthesize knowledge on antecedents and value potentials related to process mining use. We then incorporate the identified antecedents and value potentials as well as characteristics reflecting their manifestations in a taxonomy, which enables classifying the effort for establishing the antecedents and expected value potentials of process mining for a cost-benefit evaluation of process mining use cases. We finally evaluate the taxonomy by applying it to assess four use cases at a German manufacturing firm. The resulting taxonomy comprises antecedents and value potentials inherent to process mining use cases. The value potentials are reflected in the **business relevance**, that is, the importance of the use case to the organization, and the **potential**, that is, the value potentials resulting from the capabilities of process mining, of the use case. The antecedents include **organizational/project-specific antecedents**, such as resource availability and management support; **process mining-related antecedents**, such as process miner expertise and process awareness; **process-specific antecedents**, such as process size and complexity; and **IS and data-related antecedents**, such as quality and amount of raw data. We provide characteristics derived from literature and practice for each antecedent and value potential to enable operationalization and assessment.

Socio-Technical Challenges and Antecedents for the Adoption of RPA. RPA is considered a promising new means for business process automation, yet organizations struggle with successful adoption and use. Drawing on literature and the results of a case study (Yin, 2014) of an automotive organization adopting RPA, in **P4,** we reveal the socio-technical challenges that organizations experience when adopting RPA and point towards antecedents that organizations can establish to address those challenges. In particular, we show that organizations face six major socio-technical challenges that arise from the low code approach inherent to RPA that allows SMEs without IT background, also referred to as "citizen developers" (Bock & Frank, 2021), to act as developers. These challenges align with the RPA lifecycle and comprise SME’s **insufficient understanding of RPA** capabilities and requirements, the incomplete/ambiguous understanding of the **organization’s as-is processes**, the **lack of IT development knowledge and experience**, **maintenance** responsibilities in the business unit, **balancing** RPA citizen developer and operational roles, and the **administrative overhead**.

To address these socio-technical challenges and facilitate the organizational adoption of RPA, we engaged with the literature on RPA and low code development and the empirical evidence from our case study in a design science approach (Hevner, 2007) to provide recommendations on how to establish required antecedents alleviating the challenges (see Table 11).

Table 11. Proposed measures to address socio-technical RPA challenges

Phase of RPA Lifecycle	Challenge	Proposed Measures
Selection & Initialization	SME’s insufficient understanding of RPA capabilities and requirements	• *Establish a CoE* to support the initialization of RPA and process selection, e.g., by providing information on exemplary cases of RPA automation or selection guidelines

Analysis & Design	Incomplete/ambiguous understanding of the organization’s as-is processes	• *Engage with several end-user representatives* to integrate their perspectives into a comprehensive picture of the as-is process landscape • *Appoint an RPA manager* to challenge the as-is process landscape and document all surfacing information • *Engage early on with the RPA citizen developer* to assess the technical feasibility of planned projects
Implementation & Testing	Lack of IT development knowledge and experience	• *Provide training* to newly assigned RPA citizen developers by both the RPA vendor and the CoE to share firm-specific best practices • *Derive a structured implementation approach* by designing the bot and implementation schedule upfront, if needed, supported by the CoE
Operation & Maintenance	Maintenance responsibilities in the business unit	• *Preserve knowledge* on processes and RPA implementation that emerges in the project • *Ensure resource availability* by allowing RPA citizen developers to allocate time for maintenance tasks and ensure support from the CoE
Overarching	Balancing RPA citizen developer and operational roles	• *Restructure operational responsibilities* by allowing SMEs with RPA roles time for their new tasks Management and avoiding placing all roles on one SME • *Enforce an implementation schedule* to allow citizen developers to allocate time and separate these timeslots from operational tasks
	Administrative overhead	• *Appoint RPA managers* to attend to administrative requirements that unexpectedly surface

In sum, in addressing RQ1, we show that organizations need to account for socio-technical challenges when adopting diagnostic or automating business process technology by establishing organizational capabilities and practices that serve as antecedents for successful adoption. We highlight the findings for RQ1 in Table 12.

Table 12. Overview of key results of research question 1

P	Findings
P1	• Contextualization of the process mining IT artifact as a **diagnostic business process technology** within its nomological net of organizational use • Synthesis of socio-technical antecedents for the organizational adoption of process mining – Organizational capabilities: Support and commitment of senior management, expert knowledge on data preparation and analysis implementation, availability of resources, availability of raw process data, quality of raw process data, quality of event logs – Organizational practices: Structured implementation procedure and project management, careful selection of mining algorithms and focus of analysis, collaboration practices with project stakeholders and process owners, interpreting and discussing results, communicating and visualizing results

	• Overview of usage scenarios for process mining enabled by the identified socio-technical antecedents: discovery of as-is business processes, analysis of business process variants, conformance checking to detect deviations from standard process models, enhancement of existing process models, assessment of business process performance, process flow predictions • Summary of the organizational impact of process mining use: process transparency, measured process performance, increased process efficiency, enforced process conformance, improved process standardization, monitoring the effects of organizational change, forecasting of process change
P5	• Synthesis of required antecedents and expected value potentials for assessing use cases for the **diagnostic business process technology** process mining – Value potentials: business relevance (business volume and business criticality) and potentials related to process mining capabilities (transparency, conformance checking, process monitoring, performance analysis, forecasting) – Antecedents: organizational/project specific (resource availability, management support, process owner commitment, end user commitment), process mining-related (process miner expertise, process awareness), process specific (size, complexity), and IS and data-related (quality/amount/availability of raw data, quality of event log, number of IS) • Development of a taxonomy reflecting the identified antecedents and value potentials and their characteristics for enabling the cost-benefit assessment of process mining use cases • Evaluation of the taxonomy by applying it to assess four process mining use cases at the firm "Alpha"
P4	• Synthesis of socio-technical challenges for the organizational adoption of **automating business process technology**, taking the example of RPA – SME's insufficient understanding of RPA capabilities and requirements (e.g., not "understanding the bigger picture"), – the incomplete/ambiguous understanding of the organization's as-is processes (e.g., process documentation reflecting experts' "own, biased understanding of the process"), – the lack of IT development knowledge and experience (e.g., experts' "feeling lost" and lacking a structured implementation strategy), – maintenance responsibilities in the business unit (e.g., without proper documentation, experts struggle to provide continuous maintenance), – balancing RPA developer and operational roles (e.g., experts "feeling challenged by frequently transitioning between their development and operational roles") – the administrative overhead (e.g., "programming fades into the background" due to the high administrative overhead of RPA implementation). • Deriving measures for organizations to develop socio-technical antecedents alleviating the identified challenges in RPA adoption

RQ2: *How does the use of novel business process technology influence the goals and practices of business process management?*

Implications of Top-Down and Bottom-up Use of Process Mining on BPM Practices. Due to its interpretive flexibility and usability by non-IT experts (Engert et al., 2021), process mining can be implemented and leveraged on multiple organizational levels, ranging from the executive management level to the operational workforce, which results in different options for how organizations can use it to support BPM. Hence, in **P2**, drawing on a multiple case study (Yin, 2014) of four organizations of different sizes and industry settings, we identify two governance approaches for conducting process mining, i.e., a top-down or bottom-up driven implementation, that lead to different patterns of process mining use for process management on the subprocess, end-to-end process, and global process level. First, we show that the **bottom-up-driven implementation** of local process mining initiatives, that is, the organization's departments defining and implementing analyses autonomously without requirements imposed on them by the firm's management, results in the **exploratory use of process mining within departments** and the **self-organized collaboration across departments** to create cross-departmental process mining analyses. While departments use their locally available process data to conduct process mining analyses on their subprocesses, departments need to collaborate and iteratively aggregate their disparate data sources to create the database for exploring their cross-departmental end-to-end processes with process mining. Second, we show that the **top-down governed implementation** of process mining, that is, a central authority deciding on application areas and standardized analyses, leads to organizations using process mining for **standardized monitoring of processes within departments** and the **aggregation and communication of process knowledge** on an end-to-end and global level through central instances. To this end, organizations anchor and incentivize the use of standardized process mining analyses within departments, for example, by financial compensation or reporting structures, and concurrently establish central authorities, such as process owners or Chief Process Officers, responsible for aggregating and communicating process knowledge from and to the departments. In both the top-down- and bottom-up-governed implementation approach, process mining is facilitated by establishing a process mining CoE and providing data literacy training to the workforce.

Managing Decentralized RPA Implementation and Its Impact on Process Automation. Enabled by the low code paradigm, RPA can be implemented by SMEs without IT expertise leading to local ownership of RPA by business units (Bock & Frank, 2021). While this decentralized governance of RPA promises scalability, it can also lead to challenges in the implementation, control, maintenance, and use of RPA (Osmundsen et al., 2019). Addressing these challenges, in **P4,** we build on empirical data and the results of a design science research approach (Hevner, 2007) at an automotive organization implementing RPA to provide insights into how organizations can manage the decentralized governance of RPA and its effects on structures, roles, and practices related to business process automation. First, we identify four roles that are fundamental to the decentralized RPA approach: **end-users,** who are the SMEs in a business unit using and working with the bot; the **RPA manager,** who is located in the business unit and is responsible for managing the RPA project and providing administrative support until the bot is deployed; the **RPA citizen developer**, who is an SME, usually without IT background, located in the business unit and developing and maintaining the bot; and the **RPA CoE** responsible for providing technical support, training, and overseeing all RPA projects. Second, we derive a **software development framework** that outlines the responsibilities of each role during decentralized RPA development and **when and how the roles need to collaborate**. For example, the design of an RPA bot for a local use case should not only be developed by the RPA citizen developer, but also with the support of the CoE to create synergies across use cases, of the RPA manager to attend to administrative challenges with the IT department, and of the end-users to clarify processual ambiguities.

Table 13. Overview of key results of research question 2

P	Findings
P2	• Identification of two governance approaches for conducting process mining as **diagnostic business process technology**, i.e., a top-down or bottom-up driven implementation, that lead to different patterns of process mining use for process management on the subprocess, end-to-end process, and global process level • Process mining use under bottom-up governance (i.e., the organization's departments defining and implementing analyses autonomously without requirements imposed on them by the firm's management): – Subprocess level: exploratory use of process mining within departments by using locally available process data – End-to-end-process level: self-organized collaboration across departments to create cross-departmental process mining analyses by iteratively integrating disparate data sources – No use of process mining on the global process level was observed • Process mining use under top-down governance (i.e., central authority deciding on application areas for process mining and standardized analyses): – Subprocess level: standardized monitoring of processes within departments by using process mining according to pre-defined rules and KPIs – End-to-end process level: aggregating local process knowledge from process mining on an end-to-end level through a central process authority, such as process owners, and communicating it top-down to departments – Global process level: aggregating end-to-end process knowledge from process mining on a global through a central process authority, such as process owners, and democratizing access to global process knowledge • Establishing a process mining CoE and providing data literacy training to the workforce as moderating factors on process mining use independent of the chosen governance approach
P4	• Development of a software development framework for managing the influence of decentralized governance of RPA on structures, roles, and practices related to the implementation and use of RPA as **automating business process technology** – Synthesis of the phases of decentralized RPA development from the literature on RPA: selection & initialization, analysis & design, implementation & testing, operation & maintenance – Identification of fundamental roles of decentralized RPA development from the literature and the case study: end-users (SMEs in a business unit using and working with the bot, yet, usually without IT background), RPA citizen developer (SME located in the business unit who usually lacks IT background but receives RPA training and is responsible for bot development and maintenance), RPA manager (located in the business unit and responsible for managing the RPA project and providing administrative support), RPA CoE (responsible for providing technical support, training, and overseeing all RPA projects) – Specification of the responsibilities of each role in each phase and their interaction

RQ3: *What are the implications of using novel business process technology on organizational awareness about and redesign of business processes?*

Creating Process Awareness and Process Redesign Through Process Mining. As there is only sparse knowledge on how organizations transform their processes using process mining (Badakhshan et al., 2022), in **P2,** we draw on the results of a multiple case study (Yin, 2014) of four organizations to reveal how organizations achieve increased process awareness by using process mining. In particular, we focus on process awareness as the outcome because it is considered the starting point for organizations to shift their focus toward comprehensive BPM and process optimization (Kohlbacher, 2010). We show that organizations, depending on the chosen governance approach of process mining (see RQ2), create either **standardized** or **shared awareness** of subprocesses, end-to-end processes, and the firm's process landscape by using process mining which results in either **increased process efficiency**, **realization of process synergies**, **improved cross-organizational collaboration**, or **increased process alignment**. In particular, our findings indicate that the top-down governed process mining use of pre-defined analyses leads organizations to create standardized awareness of their process within and across departments and on the global process level. Building on the standardized awareness, organizations then change their processes to account for intra- and cross departmental process efficiency and synergy gains as well as improved cross-organizational collaboration. In addition, our results show that the bottom-up governed exploratory use of process mining leads organizations to create awareness of sub-, respectively end-to-end processes shared within, respectively across departments, however, without creating process awareness on a global level. As a result of the shared awareness, departments then change and align their processes on a sub- and end-to-end process level.

Creating Process Awareness Across Organizations Through Process Mining in the Context of M&A. In **P6**, we explore a novel and promising application context for process mining by operationalizing, designing, and implementing process mining analyses to assess IT-enabled processes across organizations in the context of IT DD for M&A transactions. We are motivated by the observation that the IT DD, which is the buyer's analysis of the target's IT infrastructure before closing an M&A deal, is challenged by the new responsibility of assessing the target's IT-enabled processes and developing scenarios for post-merger process harmonization. However, the IT DD lacks guidance and methods to conduct such a process assessment, particularly across the buyer and target firms. Thus, we adopt a design science research approach to uncover and translate the expectations for assessing processes in IT DD into actionable requirements for creating process awareness across buyer and target in the context of M&A transactions.

To this end, we first identify requirements for assessing processes in the context of IT DD by engaging with literature and experts. Four areas of requirements emerged as salient, in particular, measuring the **internal process performance**, the **financial and customer performance**, the **learning and growth performance**, and **process conformance**. Upon operationalizing all requirements through process assessment indicators, we use real event data from four firms to demonstrate how process mining analyses create transparency and awareness of processes across the buyer and target firm and support the assessment and cross-organizational comparison of the buyer's and the target's processes based on the identified requirements and operationalized indicators. Finally, we derive eight design principles and four enabling factors that offer guidance for the effective design, implementation, and use of process mining in the context of process assessment across firms within IT DD.

Redesigning Processes Through Process Automation with Smart Contracts. Smart contracts, which are programmed if-else conditions deployed on the blockchain, promise a secure and transparent way to automate processes according to predefined rules and without the need to trust a third party to intermediate the transaction (Cuccuru, 2017; Swan, 2015). However, smart contract adoption is only slowly increasing (Clougherty Jones et al., 2019), underlining that it is unclear if smart contracts genuinely offer new opportunities for process redesign and automation. Thus, in **P3,** we draw on an exploratory case study (Yin, 2014) of four start-ups using smart contracts to automate part of their value generation process to show how process designs changed as a result of smart contract-based automation. We reveal two pathways of process redesign enabled by smart contracts. First, we show that organizations use smart contracts to redesign their processes to **skip previously necessary intermediaries** for process execution. For example, the organization InsurCorp[6] uses smart contracts to disintermediate brokers and even the insurance company, so the customer only interacts with the smart contract. Second, we show that organizations leverage smart contracts to redesign processes to **consist of fewer manual process steps**. For example, SecurCorp[7] draws on smart contracts to automatically execute predefined actions that enable the previously manual matching of service providers and customers in the anti-malware market.

Table 14. Overview of key results of research question 3

P	Findings
P2	• Analysis of the implications of the organizational use of process mining as **diagnostic business process technology** on the creation of process awareness: – Top-down governed standardized process mining use resulting in standardized process awareness on the subprocess, end-to-end process, and global process level – Bottom-up governed exploratory process mining use resulting in shared process awareness on the subprocess and end-to-end process level but not on the global process level • Analysis of the implications of process awareness on organizational process redesign: – Standardized awareness ...of intra-departmental subprocesses leading to increased subprocess efficiency / ...of cross-departmental end-to-end processes leading to increased end-to-end process efficiency and realization of end-to-end process synergies / ...of global process variations and dependencies leading to optimized cross-organizational collaboration and realization of cross-divisional process synergies – Shared awareness ...of intra-departmental subprocess dependencies leading to increased intradepartmental process alignment / ...of intra-departmental subprocesses from the customer's perspective leading to increased awareness of customer needs within subprocesses / ...of the end-to-end customer journey leading to improved response to customer needs within

[6] We use InsurCorp as a pseudonym for a German start-up founded in 2016 that offers a smart contract-based platform for decentralized insurance products.
[7] We use SecurCorp as a pseudonym for a start-up founded in 2017 in the US that offers a decentralized marketplace for threat intelligence using smart contracts.

	subprocesses and end-to-end processes / ...of end-to-end process interrelations leading to increased cross-departmental process alignment
P6	• Design and implementation of process mining as a **diagnostic business process technology** for the assessment of IT-enabled processes at the buyer and target firms in the context of M&A • Identification and operationalization of requirements for the assessment of IT-enabled processes during the IT DD analysis, in particular, the assessment of internal process performance, financial and customer performance, learning and growth performance, and process conformance • Demonstration of process mining for measuring the identified and operationalized requirements based on real process data from four organizations • Development of eight design principles and four enabling factors for the effective design, implementation, and use of process mining for process assessment across firms within IT DD – Design principles: principles for analysis design (1. analysis of internal process performance, 2. analysis of financial & customer performance, 3. analysis of learning & growth performance, 4. analysis of conformance, 5. cross-organizational analysis); principles for analysis implementation (6. data access, 7. data anonymization, 8. data merger) – Enabling factors: pre-deal exclusiveness; prioritization of processes; joint validation of analyses; synergies with additional DD streams
P3	• Analysis of the implications of blockchain-based smart contracts as **automating business process technology** on organizational process redesign • Identification of two pathways for redesigning processes through the use of smart contracts: – Automation through disintermediation by redesigning the process to skip intermediaries whose activities are automatically executed by the smart contract (however, due to strict regulations in specific industries, such as the real estate market, currently not all intermediaries can be eliminated with smart contracts) – Automation through reducing manual process steps by providing new means for automated and secure data tracking and distribution

11 Discussion

Based on the summary of the findings, we discuss in the following how this dissertation expands our theoretical understanding of how BPM unfolds in the era of digital transformation by revealing three shifts in BPM fueled by the use of novel diagnostic and automating business process technology: (1) the shift from the centralized to the democratized adoption of BPM practices, (2) the shift from top-down process control to bottom-up process innovation, and (3) the shift from intra- to inter-organizational process awareness and redesign.

11.1 Opportunities for Business Process Management in the Era of Digital Transformation

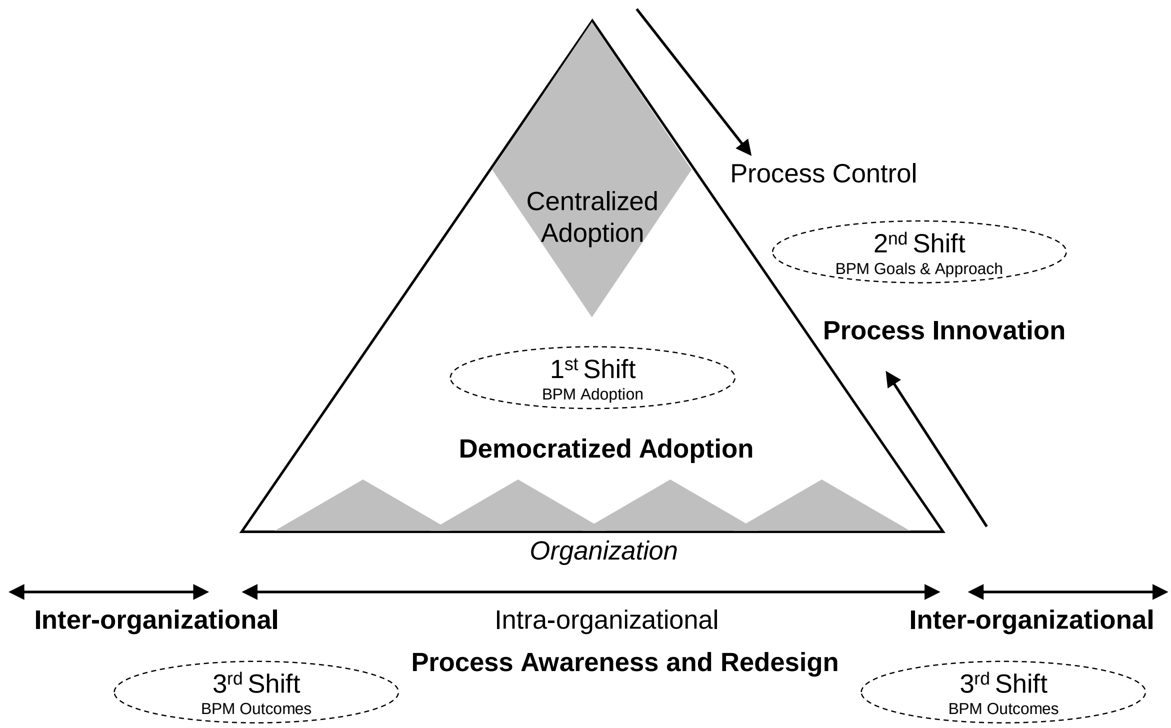
Digital transformation has a sustainable impact on how organizations manage and will manage their business processes (Baiyere et al., 2020; Mendling et al., 2020). On the one hand, digital transformation and its inherent rapid shifts in organizations' environments force them to sense required changes early on and adapt their internal workings accordingly (Hammer, 2015). As a result, the context of BPM once assumed to be relatively stable and grounded in pre-defined processes designed as solutions to organizational problems, is fundamentally changing (Baiyere et al., 2020; Mendling et al., 2020). On the other hand, digital transformation also offers unprecedented technological opportunities for organizations to monitor, analyze, automate, and improve their processes (Mendling et al., 2020; Mikalef & Krogstie, 2020). In addition, driven by new development paradigms such as low code (Bock & Frank, 2021), these digital options for process management allow various organizational groups to involve themselves in BPM.

However, even though the digital transformation presents a novel and unavoidable context for BPM, we still know only little about its ramifications for BPM (Baiyere et al., 2020; Klun & Trkman, 2018). Only recently, the first studies began to explore BPM under the paradigm of digital transformation and point toward important implications, such as finding the balance between standard processes and emergent process changes (Mendling et al., 2020) and technology-enabled opportunities for BPM practices (Kirchmer, 2021; Mikalef & Krogstie, 2020). However, these studies are the beginning of shedding light on the implications of novel digital technologies for transforming business processes and BPM (Mendling et al., 2020; Wamba, 2017). Thus, we still lack knowledge of the opportunities for BPM brought about by digital transformation.

This dissertation contributes to addressing this gap by illuminating three shifts in BPM that are currently unfolding, driven by the emergence of novel digital business process technologies (see Figure 13). To this end, we focus on recent developments in the fields of diagnostic and automating business process technology and reveal how organizations adopt and implement these technologies and how their use presents organizations with novel opportunities for the design and management of business processes. First, our findings indicate that driven by the capabilities of novel business process technology, such as their independence of specific source systems, the adoption of BPM practices in organizations shifts from a formerly centralized to a democratized approach. However, this democratized approach also poses new challenges and complexities to organizations, thus, requiring them to provide necessary antecedents to ensure successful adoption. Second, our research highlights that through the democratized, bottom-up driven use of novel business process technology in organizations, the goals of their BPM practices shift from centrally controlling the adherence to pre-defined processes to also including dynamic, decentralized process innovation. Third, our studies find that novel business process technology allows organizations not only to understand and redesign processes within their organizational boundaries at the intra-organizational level but also end-to-end processes across organizational boundaries at the inter-organizational level.

It is to be noted, however, that our results also show that none of the three shifts represents a binary decision from the old to the new world but that each shift lies on a continuum. Thus, while organizations might substitute former BPM practices with new technology-driven ones, they also continue existing practices and complement those with novel technologies. We will discuss the implications of each shift in the following.

Figure 13. Three shifts in BPM driven by the use of novel business process technology (own illustration)



11.2 1st Shift: From Centralized to Democratized Adoption of Business Process Management Practices

First, our findings show that the use of novel diagnostic and automating business process technology allows organizations to shift from a primarily centralized approach to BPM to a more democratized BPM approach.

Traditionally, BPM unfolds over the enterprise, process, and implementation levels and is driven by the centralized definition and adoption of a BPM strategy (vom Brocke & Roseman, 2015, p. 68). Thus, the firm's management and process owners play a crucial role in shaping the organization's processes and ensuring their conforming, efficient execution across the organization (Dumas et al., 2013, pp. 25-26). However, this traditional, centralized BPM approach mirrors underlying assumptions that have been inherent to BPM since before the expedited progress of digital transformation. First, the centralized BPM approach assumes the prevalence of a centralized, top-down-driven definition of process goals and designs to guide BPM practices (Baiyere et al., 2020). Second, it assumes aligning the organization's underlying infrastructure with business processes to mirror process changes (Baiyere et al., 2020). Third, it assumes that process participants' activities are centrally guided by pre-defined procedures and monitored for conforming execution (Baiyere et al., 2020). However, recent developments driven by digital transformation indicate that these assumptions are no longer valid beyond question. For example, digital transformation leads to new process designs, new roles in processes, and more frequent and dynamic changes in processes than ever before (Baiyere et al., 2020; Mendling et al., 2020). Consequently, it remained unclear thus far how the emergence of novel digital technologies, particularly in the context of business processes, influences the adoption of traditional BPM practices.

Our research contributes to closing this gap by providing insights into how using novel business process technologies leads to shifting the primarily centralized adoption of traditional BPM to a more democratized adoption of contemporary BPM. Taking the example of process mining as an important contemporary diagnostic business process technology in **P2**, we show how organizations use process mining, enabled by its technological versatility and low code approach, across hierarchical levels and roles to analyze, monitor, and change processes. Consequently, BPM practices to define and implement processes are no longer adopted only at the enterprise or process levels by managers and process owners (Dumas et al., 2013, pp. 25-26; vom Brocke & Roseman, 2015, pp. 55-60). Instead, BPM practices are also decentrally adopted at the implementation level by process participants who independently take responsibility to control and shape their processes, enabled by the unprecedented process transparency provided by process mining.

We observe a similar transformation in the context of automating business process technology, as indicated by the findings of **P4**. Facilitated by the low code approach inherent to RPA, the use of RPA allows employees from different hierarchy levels and backgrounds—particularly SMEs without IT expertise—to design, implement, and maintain automation of their processes. As a result, BPM practices to process automation become more democratized and available to employees across the organization, independent of the support of process or IT professionals to define and implement changes in the organization's IT infrastructure.

Yet, our findings also show that novel business process technology, such as process mining, can be adopted in a centralized approach, with management defining analyses and goals on the enterprise level and the organization executing the analyses accordingly, as illustrated by **P2**. While this approach resembles the traditional BPM approach, our study highlights that the transparency generated by the centrally defined process mining analyses still provides employees across the organization with the foundation to reflect on and change their processes. Consequently, employees are enabled to make informed decisions and adopt BPM practices to improve and change their processes.

In addition, our findings indicate that the decentralized adoption of business process technology and, thus, the decentralized, technology-enabled adoption of BPM practices poses organizational challenges and the need for establishing adequate antecedents. Taking the example of process mining, our insights from **P5** and **P1** point toward the relevance of establishing organizational capabilities and practices to leverage the democratized adoption of process mining. In particular, organizations need to ensure resource availability which manifests in the right skillset, time, and mindset in the workforce to engage with process mining as well as the commitment of process participants and process owners to conduct the analyses. Additionally, collaborative practices are required as employees from different departments must collaborate to collect, prepare, and analyze process data and jointly interpret the results. That also requires organizations to overcome silo-thinking and foster self-organization for cross-departmental cooperation that is not centrally initiated and controlled by management or a BPM team. Similarly, the results of **P4** extend these implications to the context of automating business process technology through the example of decentralized RPA adoption. Our findings show that organizations must provide antecedents, such as training, knowledge management, and resource availability, to ensure SMEs can independently adopt and use RPA to automate their processes.

11.3 2nd Shift: From Top-down Process Control to Bottom-up Process Innovation

Second, our findings indicate that the use of novel diagnostic and automating business process technology allows organizations to shift their BPM from the primary goal of controlling business processes in a top-down approach to also facilitating bottom-up process innovation.

Traditional BPM has focused on identifying, improving, and controlling processes to reduce process variation and increase process efficiency (Benner & Tushman, 2003; Mendling et al., 2020). These goals, rooted in the principles of scientific management and further developed in the industrial context of Total Quality Management and Six Sigma (Paim et al., 2008), proved valuable in reactively rationalizing and streamlining organizational processes (Benner & Tushman, 2003; Kerpedzhiev et al., 2021). Yet, over time the question emerged in research and practice as to whether these goals do justice to the inherent need of organizations to adapt, change, and innovate, particularly during times of turbulence and transformation (Benner & Tushman, 2003). These questions are substantiated by findings from the field of organizational routines showing that business processes are less stable than assumed and instead a source of continuous change and flexibility (Feldman, 2000; Feldman & Pentland, 2003). This tendency is exacerbated by the various options offered by novel digital technologies for more flexible, malleable process designs that can emerge ad-hoc rather than planned top-down (Baiyere et al., 2020). Consequently, organizations nowadays are challenged to account not only for top-down process control but also to foster process innovation and change (Kerpedzhiev et al., 2021). However, research is only beginning to sense this transformation in the underlying logic of BPM goals and it remains to be understood how to support and achieve the necessary change (Mendling et al., 2020).

The findings of this dissertation address this gap by offering insights into how the use of novel business process technology enables organizations to shift their BPM goals from top-down process control also to include bottom-up process innovation. Taking the example of process mining at different organizations, **P2** sheds light on how organizations use process mining to enable top-down-driven process control and bottom-up-driven process exploration. First, organizations engage in top-down-driven use of process mining, such that a central authority decides how process mining is applied in a standardized way, and departments perform the analyses accordingly. As a result, process mining enables the organization to control its processes according to pre-defined measures based on a standardized, shared process awareness within and across departments. However, the organization might simultaneously struggle to establish self-governed, exploratory use of process mining that allows the discovery of unknown process complications and the invention of new process designs.

Therefore, **P2** shows that organizations can also engage in bottom-up-driven use of process mining, such that departments are free to define and implement process mining analyses autonomously without pre-defined requirements. As a result, the departments explore, adapt, and share their analyses to achieve and modulate increased awareness of processes within and across the functional organization. The awareness then serves as the foundation for departments to not only address known process problems but also to develop new process designs in a self-governed approach. Yet, for this bottom-up approach to succeed, our study shows that employees' technical and conceptual enablement is crucial to support them in using process mining and acting on its findings. This finding is supported by the first studies on bottom-up-driven, people-centric approaches to BPM, which emphasize the importance of including and enabling operational employees to transform the firm's processes (Bruno et al., 2011; Prilla & Nolte, 2012). However, to achieve process transformation and innovation not only on the departmental but also on the organizational level, the findings of **P2** also show that top-down efforts in collecting and disseminating process mining results remain indispensable. Thus, combining the top-down- and bottom-up-driven approaches to process mining use could provide a promising avenue for organizations to reap the benefits of bottom-up-driven process innovation while ensuring the top-down-driven control and governance of business processes.

In a similar vein, the results of **P4** point toward the potential of RPA as another example of novel business process technology to enable the bottom-up-driven innovation of business processes. The low code-based approach of RPA allows employees without an IT background to leverage the technology to automate their processes, thus, shifting the formerly top-down-driven development and governance of process automation—led by the IT department and process managers—to employees on the operational level. Research on RPA corroborates this development by highlighting the potential of RPA to allow for decentralized process automation (Bygstad, 2017; Osmundsen et al., 2019; Penttinen et al., 2018). Our findings show that this transition enables organizations to leverage the comprehensive process knowledge of operational employees to identify opportunities for process automation and develop novel process designs. At the same time, the decentralized and bottom-up-driven approach to process automation challenges organizations to establish new means for governing and maintaining the resulting variety of decentral process automations.

11.4 3rd Shift: From Intra- to Inter-Organizational Process Awareness and Redesign

Third, our results show that the use of novel diagnostic and automating business process technology allows organizations to leverage their BPM practices not only for improving intra-organizational processes but also for improving inter-organizational processes.

Driven by the idea of process orientation, BPM practices have long focused on enabling organizations to restructure and reorient their inner workings in alignment with their end-to-end processes (Gaitanides, 2012; Kohlbacher, 2010). To this end, improving end-to-end processes, for example, based on awareness of process complications and redesign, is considered a target outcome of BPM (vom Brocke & Roseman, 2015, p. 124). However, the literature on BPM shows that toward this end, end-to-end processes have been primarily considered within the boundaries of organizations as "*those processes that interface with customers and suppliers of the organization*" (Dumas et al., 2013, p. 49). Thus, the focus of BPM has been on the intra-organizational perspective to understand and improve how the organization processes input from suppliers for selling it to customers (Dumas et al., 2013, p. 368). Yet, the quality of the organization's internal processes is inevitably influenced by the quality of the external processes (Dumas et al., 2013, p. 368). For example, an organization's order-to-cash process also relies on the timely and correct shipment of goods from suppliers and the efficient sales and delivery of products to customers through sales and logistics partners. Therefore, BPM scholars have been calling for research to explore potential solutions to expanding BPM to the inter-organizational context across firm boundaries (Breu et al., 2013; Legner & Wende, 2007; vom Brocke & Roseman, 2015, p. 124). However, various studies point toward the challenges of inter-organizational BPM. For example, inter-organizational processes are difficult to monitor due to their distributed nature and reliance on various IT systems accounted for by different organizations (Breu et al., 2013). In addition, verifying inter-organizational processes for conformance or (un)desired change is complicated because different parties are responsible for different parts of the process, and their behavior might be intransparent to others (Breu et al., 2013; Legner & Wende, 2007). Moreover, responsibilities within the inter-organizational process, particularly at interfaces between organizations, remain unclear, hence, confounding decision rights, trust, and long-term strategic coordination (Legner & Wende, 2007). Consequently, realizing inter-organizational BPM and improvements remains challenging to research and practice (Buchinger et al., 2022).

The results of this dissertation contribute to closing this gap by providing insights into how the use of novel business process technology allows organizations to achieve redesign and automation of not only intra-organizational but also inter-organizational business processes. Revisiting the example of process mining as a novel diagnostic business process technology, the findings of **P2** indicate that the use of process mining can lead to increased awareness and improvement of inter-organizational processes by offering transparency, in particular, on previously neglected inter-organizational process interfaces, such as handover points between suppliers and the focal firm. However, to succeed, organizations need to foster mechanisms for assigning responsibilities and collecting process data on the organizational level from across departments and, if possible, from external organizations to generate end-to-end process transparency. We extend these implications with the findings of **P6**, which indicate that particularly cross-organizational process mining can further the understanding and redesign of inter-organizational processes. Cross-organizational process mining refers to the data-driven analysis of either the collaborative process between multiple organizations or similar processes executed by multiple organizations (van der Aalst et al., 2012). In **P6**, we demonstrate the data preparation, design, and implementation of cross-organizational process mining analyses in the context of M&A transactions to facilitate awareness and comparison of the buyer's and the target's processes. Additionally, we point toward challenges that might emerge when applying cross-organizational process mining in a particularly sensitive setting such as M&A and provide guidance on how to address these challenges, for example, through establishing the contractual basis for sharing sensitive process data and anonymizing data when possible. These findings could also prove valuable for analyzing collaborative inter-organizational processes with process mining, where multiple organizations must share process data and potentially sensitive information to optimize the overall end-to-end process.

We extend these findings to the context of novel automating business process technology by taking the example of DLT. Thus, in **P3,** we show how the unique technological capabilities of DLT and smart contracts support organizations in redesigning inter-organizational processes for automation. Our results indicate that smart contracts provide the required decentralized infrastructure across organizations to enable the design and execution of inter-organizational processes without having to agree on a third-party provider. To this end, pre-defined actions are specified in the smart contract and automatically executed when certain conditions are met. Thus, the automation rules are transparent to all involved parties, which furthers trust between the parties and in the process and provides a baseline to monitor and improve. These implications resonate with previous studies that demonstrated the suitability of blockchain-based systems for cross-organizational process management and automation by providing a common and transparent infrastructure (Fridgen et al., 2018).

12 Implications

The qualitative research strategy (Denzin & Lincoln, 2018b) adopted in this dissertation allowed us to shed light on how organizations can adopt and implement novel business process technology and how these technologies influence their BPM practices. As a result, this dissertation provides several implications for theory and practice. In the following, we discuss how our findings contribute to research on (1) the organizational adoption and (2) the use of business process technology and research on (3) BPM in the context of digital transformation. Additionally, we discuss how this dissertation provides practitioners with implications on how to tackle the challenges of adopting novel business process technology and guidance on how, when, and why to use these technologies in order to advance and improve their BPM practices.

12.1 Implications for Theory

First, the findings of this dissertation contribute to **research on the organizational adoption of business process technology** by synthesizing and operationalizing antecedents for the adoption of novel diagnostic and automating business process technologies while also highlighting potential challenges. Due to their recent emergence, literature on novel business process technologies, such as process mining and RPA, has primarily focused on discovering technical facets of organizational adoption, such as the necessary data quality for process diagnosis (van der Aalst et al., 2012) or the technical infrastructure for process automation (Issac et al., 2018). In contrast, socio-technical antecedents, such as required organizational structures, practices, and governance approaches, have, despite their well-established importance for successful IS implementation (Poon & Wagner, 2001), remained largely unaddressed (Badakhshan et al., 2022; Grisold et al., 2020). Yet, anecdotal evidence points to the practical importance of systematically understanding antecedents for adopting business process technology. For example, process mining can be applied to various IT systems providing event data, thus, challenging organizations to identify and prepare for valuable use cases (Grisold et al., 2020; van der Aalst, 2016). Similarly, RPA can be implemented on various IT systems in a hybrid or decentralized setting, which deviates from the traditional centralized IT development setting, hence, challenging organizations to prepare for and govern RPA adoption (Hofmann et al., 2020; Lacity & Willcocks, 2016a; Syed, Suriadi, et al., 2020).

Therefore, this dissertation contributes to addressing this gap twofold. On the one hand, we synthesize and structure extant knowledge on antecedents for adopting business process technology, particularly for process mining in **P1** and **P5** and for RPA in **P4**. Additionally, we corroborate these findings with insights from practice by leveraging case studies. As a result, we delineate and characterize organizational practices and capabilities as well as process- and technology-specific socio-technical antecedents for successfully adopting business process technology. Furthermore, we provide a structured framework for operationalizing and measuring the necessary antecedents grounded in the taxonomy we developed in **P5**. We also point toward the interplay between antecedents and their implications for the organizational adoption of business process technology in **P1**. On the other hand, we provide insights into challenges that organizations experience while adopting business process technology and potential measures to overcome them. Taking the example of process mining in **P2**, we point toward socio-technical challenges such as dealing with increased transparency through process mining and creating a shared language to jointly interpret process mining findings. In the context of RPA in **P4**, we reveal challenges that result from the decentralized adoption of RPA, i.e., SMEs develop their RPA bots, such as coping with maintenance responsibilities and balancing RPA and operational roles. To address these challenges, in **P4**, we present a framework for decentralized RPA development acknowledging the identified socio-technical challenges. We thereby synthesize and extend previous studies providing the first insights into success factors and challenges for the adoption of process mining (Mans et al., 2013; Syed, Leemans, et al., 2020) and RPA (Hofmann et al., 2020; Syed, Suriadi, et al., 2020). Consequently, we sensitize scholars to the importance of socio-technical antecedents when investigating the (un)successful adoption of business process technology and the need to address the unique requirements and challenges these technologies pose for organizations.

Second, this dissertation contributes to **research on organizational value realization from business process technology** by shedding light on the underlying mechanisms of how organizations implement and benefit from novel diagnostic and automating business process technologies. Only recently, a growing body of research has recognized the application of novel business process technologies, such as process mining, RPA, and DLT, in an organizational context (Grisold et al., 2020; Herm et al., 2020; Khan et al., 2021; Santos et al., 2020; Thiede et al., 2018). However, most of the research adopts either a technological perspective on implementing these technologies in an organizational context (Leshob et al., 2018; Rojas et al., 2016) or provides insights into specific use cases, for example, depending on the industry (Dakic et al., 2018) or organizational setting (Osmundsen et al., 2019). Thus, while applying novel business process technologies in organizations has advanced technologically, we still do not understand how and why organizations leverage these technologies to create value. For example, process mining provides organizations unprecedented process transparency (van der Aalst, 2016), while RPA offers the cost-efficient automation of processes on a task level that was considered unrealizable before (Willcocks & Lacity, 2016). Yet, we lack an understanding of how organizations engage with these capabilities to create monetary and non-monetary value.

Acknowledging this gap, this dissertation contributes to literature twofold. First, we provide insights, grounded in literature and practice, on how and to what end organizations implement novel business process technologies, thereby shedding light on the underlying mechanisms of value creation, in particular, related to the use of process mining in **P1**, **P2**, **P5**, and **P6**, RPA in **P4**, and DLT in **P3**. We systematically reveal the reasons why organizations adopt novel diagnostic or automating business process technologies and relate these to mechanisms of implementing and using the technologies. For example, organizations strive to increase process transparency and efficiency and hence, use process mining to encourage bottom-up exploration of cross-departmental processes and RPA to decentrally automate processes driven by SMEs. Second, to attain these goals, we show how organizations leverage the flexibility and low code capabilities of novel business process technology, such as process mining and RPA. Our findings point toward how these capabilities facilitate novel mechanisms of value creation and, thus, contribute to the emerging literature on the organizational implications of novel implementation paradigms such as low code (Bock & Frank, 2021; Sahay et al., 2020). For example, we demonstrate in **P2** and **P3** how the bottom-up, decentralized use of process mining and DLT allows for the exploratory improvement of end-to-end processes based on new forms of cross-departmental and cross-organizational collaboration. Thus, our findings indicate that using novel business process technology contributes toward overcoming the historically evolved silo-thinking in functional organizations by fostering end-to-end process transparency and collaboration (McCormack & Rauseo, 2005). This is particularly valuable in the light of organizations increasing their efforts for achieving organizational process orientation in the last decades (Christiansson & Rentzhog, 2019; Kohlbacher & Reijers, 2013) but failing due to a lack of end-to-end process thinking and cross-functional collaboration (Van Looy & Devos, 2019; Vlahovic et al., 2010). In sum, the findings of this dissertation reveal how the use of novel business process technology enables organizations to create value by understanding, redesigning, and improving their end-to-end processes. As such, we encourage scholars to revisit the topic of end-to-end process improvement and orientation—which has been studied for decades yet often has proven unsuccessful as a practical concept (Grover & Markus, 2008)—under the paradigm of new technological advancements.

Third, this dissertation contributes to **research on BPM in the digital era** by revealing how BPM practices change when organizations leverage novel diagnostic and automating business process technology and how these practices result in unprecedented opportunities for process transformation. Even though digital transformation has fundamentally changed and continues to change the ways organizations manage their business processes (Baiyere et al., 2020; Mendling et al., 2020), we still know only little about its implications for BPM (Baiyere et al., 2020; Klun & Trkman, 2018). Recently, the first studies have started to investigate BPM within the context of digital transformation. These studies indicate significant implications, including the need to strike a balance between established processes and emerging process changes (Mendling et al., 2020) and the potential for new BPM practices facilitated by technology (Mikalef & Krogstie, 2020). However, these studies merely scratch the surface of understanding the effects of digital technologies on business process transformation and BPM (Mendling et al., 2020; Wamba, 2017). For example, process mining as a novel diagnostic business process technology offers unprecedented process transparency that might usher in a new era of BPM that is no longer based on subjective, incomplete process information acquired through time-consuming workshops and interviews (Dumas et al., 2013). Similarly, RPA, as a novel automating business process technology based on low code, might contribute toward democratizing BPM practices that are traditionally only available to process experts (van der Aalst et al., 2018). However, these effects are mere speculations as there is still a lack of knowledge regarding the opportunities that digital transformation presents for BPM.

We address this gap through the findings of this dissertation threefold. First, focusing on approaches for adopting BPM practices in organizations, we show how the use of novel diagnostic and automating business process technology allows organizations a more democratized adoption of BPM practices. For example, in **P2,** we demonstrate how the technological flexibility and ease of use of process mining enables organization members across roles and hierarchy levels to analyze, monitor, and change processes. Hence, BPM practices to define and implement processes are no longer adopted only at the enterprise or process levels by managers and process owners (Dumas et al., 2013, pp. 25-26; vom Brocke & Roseman, 2015, pp. 55-60). Second, relating to the goals of BPM practices, this dissertation demonstrates that the use of novel business process technology results in organizations not only monitoring their processes through traditional BPM practices in a top-down fashion but also innovating their processes from the bottom-up. For example, in **P4**, we reveal how RPA, as a low code-based automation technology, enables employees without an IT background, yet, knowledgeable on the organization's processes, to drive and engage in process redesign and automation, which was formerly led by BPM and IT experts only (Penttinen et al., 2018). Third, focusing on the outcomes of BPM practices for organizations, we shed light on how the use of novel business process technology allows organizations to expand their traditional focus on redesigning and automating intra-organizational processes to impact inter-organizational processes as well. For example, in **P3**, we show how the technological capabilities of the automating business process technologies DLT and smart contracts facilitate the redesign and automation of inter-organizational processes without the need for a trusted third-party provider. Hence, this dissertation provides scholars with an overview of profound shifts in traditional BPM practices enabled by the capabilities of novel digital technologies. As such, we deepen and expand initial studies pointing toward the transformational effect of digital technology on BPM (Martin et al., 2021; Mikalef & Krogstie, 2020) and follow calls to understand how BPM changes in the era of digital transformation (Baiyere et al., 2020; Mendling et al., 2020).

12.2 Implications for Practice

The discipline of BPM is inextricably interwoven with practice and serves the goal of supporting organizations to achieve the management of their business processes as a driver of profitability and innovation. Therefore, this dissertation provides several practical implications and actionable insights for practitioners.

First, acknowledging the practical challenges that organizations experience when adopting novel business process technology, we provide practitioners with a **deepened and systematic understanding of antecedents for successful business process technology adoption**. To this end, we focus on process mining, RPA, and DLT as three emerging business process technologies of high relevance and great practical interest so that our findings apply to the current technological environment in organizations. Drawing on literature and insights from case studies, we point practitioners toward factors to consider when planning to implement novel business process technology and potential challenges that can arise. Taking the example of process mining, we incorporated our findings on antecedents in a structured, actionable framework that enables practitioners to identify and measure the requirements for implementing specific process mining use cases. Moreover, we also acknowledge the socio-technical challenges faced by organizations when adopting process mining due to transparency-induced skepticism and restraint in the workforce. To alleviate these challenges, we point toward measures to address these concerns that have proven valuable in the context of the organizations we studied. Similarly, taking the example of RPA, we developed a process framework to guide practitioners in understanding, selecting, and implementing the roles, responsibilities, and actions necessary for adopting decentralized RPA. Finally, we ensured to shed light on challenges that can occur during the adoption of business process technology, such as lack of data or skills in the workforce and defined preparatory measures to address these challenges before they arise.

Second, we offer practitioners guidance on **how, when, and why to use** novel business process technologies to address the increasing variety of potential application scenarios for these technologies and the ambiguity surrounding their value creation. Re-visiting the examples of process mining, RPA, and DLT, we provide practitioners with use cases, potential benefits, and paths to value creation in various organizational and industry settings. For example, focusing on process mining, we show how the technology can be leveraged to facilitate the DD phase in M&A transactions as an application scenario that has not been considered before (even regarding other technological support options). In addition to prototypical process mining analyses, we offer practitioners a framework for operationalizing process performance indicators for implementation in process mining and design principles to navigate the implementation of valuable process mining analyses. Hence, we give practitioners the foundation and the flexibility to design and use process mining for process assessments on their particular dimensions of interest, depending on the context of the use case. In a similar vein, taking the example of DLT, we show practitioners how the use of DLT and smart contracts allows them to achieve previously unfeasible redesign and automation of processes, thus, pointing them toward novel use cases and value potentials. At the same time, we also give insights into the potential drawbacks of choosing DLT and smart contracts over traditional means of process automation, such as ERP systems and WfMS, in order to enable organizations to make well-informed and transparent decisions.

Third, relating to the struggles that organizations experience when redefining their BPM practices in the age of digital transformation, we provide practitioners with **insights on how they can leverage novel business process technology to advance and improve their BPM practices**. Building on findings we derived from the context of the organizational use of process mining, RPA, and DLT, we show how organizations can incorporate these technologies to achieve novel opportunities for the design and management of business processes. For example, considering process mining, we point practitioners to novel BPM practices that can be taken based on process mining to increase organizational process awareness on the sub-process, end-to-end process, or process landscape level. Different practices with different advantages and disadvantages become relevant depending on the process mining governance approach chosen, i.e., a top-down- or bottom-up-driven scenario. On a similar note, taking the example of RPA, we sensitize practitioners to new opportunities to include employees without an IT or BPM background to drive and participate in process redesign and automation actively. Hence, we support practitioners to prepare for a more democratized, bottom-up-driven management of processes facilitated by the capabilities of new business process technology.

13 Limitations

We acknowledge that this dissertation is subject to several limitations grounded in our choice of research paradigm, research methods, and data sources. While the limitations of each study are discussed in detail in the six embedded publications, we will provide an overview of the most important limitations in the following.

First, we want to point out that limitations emerge from our adopted constructivist research paradigm. In choosing a **constructivist research paradigm**, we adopted a relativist ontology, a subjectivist epistemology, and qualitative research methods (Lincoln et al., 2011). While this paradigm enabled us to inquire about the inter-subjective, lived experiences of individuals in organizations using novel business process technologies, in particular, the relativist ontology and subjectivist epistemology entail limitations of validity and generalization (Ketokivi & Mantere, 2010; Scotland, 2012).

On the one hand, **relativist ontology** assumes that multiple realities and, hence, multiple interpretations of reality exist that depend on and are constructed by the people holding them (Guba, 1990, pp. 26-27; Lincoln et al., 2011, pp. 102-103). However, this brings into question the validity of research findings created based on a relativist view of the world (Scotland, 2012). To this end, the debate around whether validity is a useful concept for measuring the soundness of constructivist research has spurred new criteria, such as fairness, as the inclusion of all perspectives relevant to the phenomenon of interest, and authenticity, as the ability to prompt action (Lincoln et al., 2011, pp. 240-243). By interviewing various stakeholders in each of our studies and deriving actionable insights, we aim to address these concerns on the validity of our research caused by subjectivist epistemology.

On the other hand, the **subjectivist epistemology** assumes an inextricable link between the researcher and the studied phenomenon such that the researcher constructs a subjective understanding of reality through their interaction with the world (Guba, 1990, pp. 26-27; Lincoln et al., 2011, p. 103). Building on this premise, unaffected and universal knowledge of the world is impossible as knowledge differs from person to person depending on their experiences and interactions with the world (Levers, 2013; Scotland, 2012). This complication is also reflected in our underlying inductive reasoning approach to studying the world based on a subjectivist epistemology (Ketokivi & Mantere, 2010). As inductive reasoning draws on the observation of and interaction with specific cases (performed by individuals who shape the observations and knowledge they derive), researchers can never observe generalities and unequivocally claim universal truth (Ketokivi & Mantere, 2010). Consequently, research based on a subjectivist epistemology is subject to limited transferability as results are fragmented, context-specific, and challenging to generalize (Scotland, 2012). On the other hand, the deep investigation of context and individual cases allows access to and the discovery of rich notions of embodied, contextual, and experiential knowledge (Ketokivi & Mantere, 2010; Lincoln et al., 2011, p. 239). Thus, we ensured to devise careful strategies for selecting the cases we studied, acknowledging their context in relation to our research endeavor, and embedded our findings within these contexts.

In addition, this dissertation is subject to limitations grounded in the chosen qualitative research methods. First, we acknowledge limitations pertaining to the **literature reviews** we conducted as a primary or secondary research method in the embedded publications. In general, our literature reviews were not exhaustive. Hence, we cannot rule out the possibility—despite careful methodological execution—of having involuntarily neglected studies of importance for our research. In addition, considering that the literature reviews focused on emerging research themes, such as process mining and RPA, we want to point out that these fields change and grow dynamically, and new studies become available every day that might contribute additional insights to our findings. Concerning the literature review we conducted in **P1**, we want to draw attention to the limitations of the assessing literature review approach (Leidner, 2018) we chose. In particular, we let our review be guided by the theory of the IT artifact in its nomological net (Benbasat & Zmud, 2003), which proved valuable in systematically unraveling value realization from process mining. However, the choice of this framework has influenced our analysis, and using a different theoretical framework might generate different results.

Second, we want to point out limitations related to our use of **case study research**. In general, the quality of case study research is reflected by the study’s construct validity (identifying correct operational measures for the concepts being studied), internal validity (seeking to establish a causal and not a spurious relationship), external validity (defining the domain to which the study’s findings can be generalized), and reliability (demonstrating that the operations of a study can be repeated with the same results) (Yin, 2014, p. 46). First, to ensure construct validity, we triangulated the data drawing on multiple sources of evidence (Flick, 2017), established a chain of evidence (Gioia et al., 2013), and ensured to validate our qualitative data with key informants (Yin, 2014, p. 47). However, we are aware that selecting different data sources might produce varying results. Second, to ensure internal validity, we relied on different analytic techniques such as pattern matching, explanation building, and addressing rival explanations (Yin, 2014, pp. 47-48). In addition, we also leveraged grounded theory coding to inductively and iteratively identify emerging themes and concepts and their interrelations from the qualitative data, in particular in **P2** and **P6** (Gioia et al., 2013; Strauss & Corbin, 1994). Yet, we acknowledge that our findings are subject to the general problem of making inferences from qualitative data, indicating that different analytic approaches might yield differing results. Third, we ensured external validity by identifying and embedding our studies in appropriate theory and relating it to our research questions (Yin, 2014, p. 48), such as the theory on process awareness in **P2** and low code development in **P4**. Still, our findings might be limited to the immediate context we studied and, thus, would need to be corroborated through future research in novel settings. Fourth, we ensured reliability by thoroughly documenting our case study procedures and relying on well-established methods, such as the strategies for conducting semi-structured expert interviews by Myers and Newman (2007) and within- and cross-case analysis by Eisenhardt (1989). However, reliability remains to be tested through the replication of our studies.

Last, we acknowledge limitations that emerge from the **design science research (and embedded taxonomy development) approaches** we conducted. In general, design science research requires the application of rigorous methods to construct and evaluate artifacts. To this end, we ensured to carefully perform and document the iterative design science research approach according to Hevner (2007) and Hevner et al. (2004), for example, for creating a development framework in **P4**, a taxonomy in **P5**, and a process mining artifact and design principles in **P6**. Yet, particularly, the design of a taxonomy can never be fully comprehensive, and the identified dimensions and characteristics depend on the chosen sources from literature and practice. In addition, we evaluated each artifact with practitioners to ensure its applicability and usefulness for practice and incorporated emerging requirements in the artifacts. Still, it was outside the scope of this thesis to evaluate the artifacts in practical use over an extended period, which, however, might provide additional insights into their usefulness and reveal the need for changes.

In sum, this dissertation is subject to several limitations that result from our choice of a constructivist research paradigm and the application of qualitative research methods. While we followed well-established methodological guidelines to address concerns, our research is still only a first step toward revealing the changes in BPM driven by digital transformation. Thus, in the next chapter, we point toward several avenues for future research building on the findings of this dissertation.

14 Future Research

Building on the findings of this dissertation, we point toward opportunities for future research on the influence of novel business process technology on BPM practices in the era of digital transformation (see Table 15).

Table 15. Avenues for future research emerging from the embedded publications

P	Questions for Future Research
P1 P4 P5	**Developing antecedents for adopting business process technology:** • How can organizations develop antecedents for adopting business process technology? • What are the reciprocal effects between organizational and technological capabilities and practices as antecedents for business process technology? **Dealing with social, ethical, and legal implications of adopting business process technology:** • How can organizations manage the impact of business process technology adoption on roles and responsibilities? • How can organizations effectively manage the ethical and legal implications of adopting business process technology, considering privacy, data protection, and automated decision-making?
P2 P4	**Managing centralized and decentralized business process technology use:** • How can organizations scale and govern the decentralized use of business process technology? • How can organizations balance the centralized and decentralized use of business process technology? **Managing top-down- and bottom-up-driven technology-enabled BPM practices:** • What structural and cultural changes are required for organizations to facilitate and establish bottom-up-driven technology-enabled BPM practices? • How can organizations balance the top-down-driven process control and bottom-up-driven process innovation enabled by business process technology?
P2 P3 P6	**Addressing challenges of inter-organizational process awareness:** • How can organizations collect and integrate process data from multiple organizations to achieve end-to-end process transparency? • How can organizations ensure comparability and integrability during inter-organizational end-to-end process analysis? **Addressing challenges of inter-organizational process automation:** • What approaches can organizations employ to maintain inter-organizational end-to-end process automation? • How can organizations address trust and privacy concerns when automating inter-organizational end-to-end processes?

First, we encourage scholars to utilize the knowledge we generated on antecedents for adopting business process technology to shed light on the **development of and the social, ethical, and legal challenges related to those antecedents**. Even though we synthesized the current state of research on required antecedents for adopting business process technology, there is still only sparse knowledge on how organizations can develop these antecedents (Hofmann et al., 2020;

Lacity & Willcocks, 2016a; Mans et al., 2013). In addition, an interplay between antecedents, such as technological and organizational capabilities and practices, might influence the success or failure of business process technology adoption. For example, the organization's IT governance practices will influence how the organization stores and handles process data (Weill & Ross, 2004). Storing and handling data in a centralized or decentralized, standardized or diversified approach will, in turn, influence how the adoption of business process technology, such as process mining, unfolds. As such, we consider it valuable for future research to investigate the development and reciprocal effects between antecedents for business process technology adoption.

In addition, our research points toward understanding the social, ethical, and legal challenges related to establishing those antecedents. On the one hand, preparing for and adopting business process technology, particularly based on a low code approach, impacts established organizational roles and responsibilities. For example, operational employees become closely involved with BPM while process and IT professionals have to transfer responsibility. Thus, we consider it important for future research to study how organizations can account for the social and structural changes that entail adopting novel business process technology. On the other hand, adopting business process technology has ethical and legal implications for organizations. For example, adopting business process technology often involves collecting, processing, and storing large amounts of process data, which might contain sensitive or private information and increase transparency on employee behavior. We know from the broader field of BDA that these effects can create an organizational backlash and hinder technology adoption (Günther et al., 2017; Richards & King, 2013). Hence, we call for scholars to reveal ethical and legal challenges and countermeasures in the process of business process technology adoption.

Second, we call for future research to leverage the insights we provided on business process technology use and its implications on BPM practices to generate deeper insights into **how organizations can manage these novel usage patterns and shifting BPM practices**. On the one hand, we encourage scholars to expand our knowledge on how organizations can manage the decentralized use of business process technology by non-IT- or non-process-professionals. We showed that through novel technological capabilities, the decentralized use of business process technology becomes possible, which differs from the centralized use of traditional business process technology. While we revealed that the decentralized use allows organizations to expand their BPM practices throughout hierarchical levels, we also foreshadowed that it bears challenges for scaling and governance. For example, organizations might experience a variety of local business process technology initiatives lacking central control, which is also reflected in recent research (Osmundsen et al., 2019). Thus, we call for scholars to study how organizations can scale and govern decentralized business process technology use and balance it with—the potentially indispensable—centralized use.

On the other hand, we point future research toward investigating how organizations can manage bottom-up-driven BPM practices, which we revealed as a consequence of using novel business process technology while balancing it with traditional top-down-driven BPM practices. While the technological capabilities of novel business process technology provide the foundation for organizations to establish bottom-up-driven BPM practices, our research also indicates the importance of structural and cultural changes in the organization. For example, employees need to create a common process language to discuss findings from business process technology, and they might require support from a central authority, such as a CoE, which is also reflected in practitioner reports (Reinkemeyer, 2020). Hence, we encourage scholars to reveal the necessary structural and cultural changes to facilitate and establish bottom-up-driven BPM practices enabled by novel technology. In addition, organizations also need to balance these novel bottom-up-driven practices with traditional top-down-driven BPM practices accounted for by BPM and IT professionals. Our studies show that while bottom-up-driven BPM practices allow for process innovation, top-down-driven BPM practices—supported by novel business process technology—remain essential to ensure process control. To this end, future research should investigate how organizations can best navigate and balance this tension.

Third, we call for future research to utilize the knowledge we generated on the outcomes of using novel business process technology for studying **how organizations can address emerging challenges of inter-organizational process awareness and automation**. While our results show that organizations use novel business process technology to improve their intra-organizational processes, we also demonstrate how they use these technologies to create awareness and automation of inter-organizational end-to-end processes. However, we acknowledge that several questions about this phenomenon remain open. On the one hand, socio-technical challenges concerning inter-organizational process awareness through business process technology remain to be addressed. For example, to apply business process technology to illuminate inter-organizational processes, we need to understand how organizations can collect and integrate process data from multiple organizations and ensure the comparability and integrability of sub-processes across organizations.

On the other hand, future research should study the socio-technical challenges of inter-organizational process automation through business process technology. For example, we call for scholars to shed light on how organizations can maintain inter-organizational process automation from a technical and business perspective and how they can address emerging trust and privacy concerns. Insights on these questions would help scholars and practitioners to leverage the capabilities of business process technology better to contribute toward the complex and ambitious goal of inter-organizational process improvement.

15 Conclusion

In recent years, organizations have been challenged to manage their business processes in the increasingly dynamic and complex context of digital transformation. Informed by these changes and digital transformation itself, novel technologies have emerged to facilitate organizational BPM. In particular, organizations are now at the disposal of novel diagnostic and automating business process technologies, such as process mining, RPA, and DLT. However, practice shows organizations still struggle to leverage these novel business process technologies to transform their processes. Therefore, in this dissertation, we investigated how organizations can adopt novel diagnostic and automating business process technology, how using these technologies enables new approaches to BPM, and how, as a result, organizations can transform their business processes.

Drawing on a qualitative research strategy, we first identified the socio-technical antecedents that enable organizations to adopt novel diagnostic and automating business process technology. Then, we shed light on new mechanisms that organizations can use to govern and manage business processes enabled by using these technologies. Last, we revealed how these mechanisms enabled by novel business process technology allow organizations to seize unprecedented opportunities for creating process awareness and redesign.

As a result, this dissertation expands our theoretical understanding of how BPM unfolds in the era of digital transformation and provides actionable implications for organizations to implement these findings. From a theoretical perspective, we reveal three shifts in BPM fueled by novel diagnostic and automating business process technology. First, we showed how the flexibility and capabilities of novel business process technology enable organizations to shift their traditionally centralized adoption of BPM practices to a more democratized approach. Second, we point toward organizations shifting their BPM goals from primarily controlling processes top-down to additionally innovating processes from the bottom up enabled by novel business process technology. Third, we indicate how the use of novel business process technology shifts the outcomes of BPM practices from pertaining only to the intra-organizational level to also including the inter-organizational level. Additionally, we provide practical implications for organizations to tackle the challenges of adopting novel business process technology and guidance on how, when, and why to use these technologies to advance and improve their BPM practices.

Business processes are at the heart of organizations, and their management and improvement are a continuous challenge that will probably persist as long as organizations exist. However, the inevitable changes through digital transformation open up new and exciting paths for organizations to shift and shape their BPM practices in innovative ways. In this light, we hope this dissertation sparks interest in the topic of digitally-enabled BPM and serves as a valuable starting point for scholars to further our knowledge on the implications of using novel business process technology and for organizations to embark on the journey of business process transformation in the digital age.

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Appendix A Supplementary Material: Interviews and Archival Data

Table 16. Data of embedded publication P2

Pseudonymized Company Name & Case Description	Position of Informant	Years of Process Mining Experience	Duration of Interview (hh:mm)	Number & Type of Archival Sources Collected for the Case
ManuCorp Multinational corporation from the electrical equipment industry with a process mining focus on internal processes	Head of Process Analytics	4 years	00:35 & 00:45	6 (case study, presentation, videos, blog entry, newspaper article)
	Regional Process Mining Manager	2 years	00:54	
	Regional CIO	8 years	00:58 & 01:02	
	IT Project Manager	3 years	00:32	
	Sales Manager	4 years	00:51	
DistriCorp German wholesaler with a process mining focus on cross-organizational processes	Chief Executive Officer	6 years	01:10	9 (presentations, videos, blog entries, case study, demonstration during interview)
	Chief Process Officer	6 years	01:02 & 00:39	
	Process Mining Developer	3 years	00:53	
	Process Owner Procurement	4 years	01:02	
	Procurement Controller	4 years	00:59	
	Process Manager Procurement	6 years	00:52	
PensionCorp Dutch company from the financial services industry with a process mining focus on cross-organizational processes	Data Scientist	2 years	00:42	7 (case studies, newspaper articles, blog entry)
	Head of Customer Analytics	4 years	00:54	
	Head of Analytics	4 years	00:34 & 00: 29	
	Project Manager Customer Processes	3 years	00:47	
AutoCorp Multinational automotive corporation with a process mining focus on internal processes	Project Manager Change Management	2.5 years	00:45	7 (presentations, video, case study, newspaper articles, demonstration during interview)
	Process Owner Development	1.5 years	00:48	
	Process Mining Developer Production	3 years	00:51	
	Process Mining Developer	3 years	00:52	
	Head of Process Mining	3 years	00:42	
Coding results: Building on 24 semi-structured expert interviews and archival sources, we derived 389 open codes, which we aggregated into 11 second-order codes and, finally, into 6 aggregate dimensions that represent the different forms of process awareness achieved by using process mining, depending on the governance approach.				

Table 17. Data of embedded publication P3

Pseudonymized Company Name & Case Description	Number of Interviews	Number of Archival Data	Demo of the Product?
ImmoCorp Switzerland-based start-up founded in 2018 operating in the real estate market. ImmoCorp uses smart contract-based technology to create tokenized, digital twins of properties that are bought or sold through the ImmoCorp platform	2	5	Yes
InsurCorp German start-up founded in 2016 offering a smart contract-based platform for decentralized insurance products, particularly a parametric flight delay insurance that enables the automated and decentralized pricing, underwriting, and processing of insurance policies for flight delays	1	5	Yes
LogiCorp Switzerland-based start-up founded in 2016 that uses smart-contract technology in combination with sensors to automatically monitor the end-to-end shipment of products under strict temperature regulation.	1	6	No
SecurCorp Founded in 2017 in the US offering a decentralized marketplace for threat intelligence using smart contracts by connecting incumbents from the anti-malware industry with threat intelligence experts	2	5	Yes
Coding results: We engaged in explanation building as an analytic technique, wherein we continuously iterated between initial explanatory propositions and the case findings to explain why organizations chose smart contracts as automation technology.			

Table 18. Data of embedded publication P4

Pseudonymized Company Name & Case Description	Number of Interviews in 1^{st} Design Science Research Iteration	Number of Interviews in 2^{nd} Design Science Research Iteration
AutoCorp Large automotive corporation (more than 100,000 employees and revenue of over 99 billion USD as of 2020) with more than six years of RPA experience in a decentralized approach	8 with SMEs involved in RPA projects and members of the firm's RPA CoE Average duration of 46 minutes Overall duration of 360 minutes	6 with SMEs involved in RPA projects and members of the firm's RPA CoE Average duration of 32 minutes Overall duration of 190 minutes
Coding results: We inductively analyzed the data in the 1^{st} iteration to understand challenges related to the roles and responsibilities of SMEs in decentralized RPA projects. In the 2^{nd} iteration, we identified roles involved in RPA projects and best practices to support SMEs in decentralized RPA projects.		

Table 19. Data of embedded publication P5

Pseudonymized Company Name & Case Description	Number of Interviews in 2nd Taxonomy Iteration	Number of Interviews in 4th Taxonomy Iteration
Alpha German manufacturing firm with 9,500 employees (2019) striving to expand their process mining application	6 with process and IS experts Average duration of 45 minutes	6 with process and IS experts Average duration of 45 minutes
Coding results: We inductively analyzed the data in the 2nd iteration to evaluate the application of the taxonomy to Alpha's order-to-cash and purchase-to-pay processes. In the 4th iteration, we evaluated the application of the taxonomy to Alpha's offer and return processes.		

Table 20. Data of embedded publication P6

Interviewee	Role	Experience	Duration	Design Science Research Iteration
Expert A	Senior Consultant Transaction Advisory	15 IT DDs	90 mins.	1st
Expert B	Senior Manager Transaction Advisory	30 IT DDs	90 mins.	1st
Expert C	Partner and Director of IT Audits	5 IT DDs	41 mins.	1st
Expert D	Senior Manager Transaction Advisory	20 IT DDs	42 mins.	1st
Expert E	Consultant IT M&A	5 IT DDs	59 mins.	2nd
Expert F	Consultant Transaction Advisory	20 IT DDs	45 mins.	2nd
Expert G	Director of IT Consulting	>100 IT DDs	62 mins.	2nd
Expert H	Senior Manager Technology M&A	>80 IT DDs	60 mins.	2nd
Expert A	Senior Consultant Transaction Advisory	15 IT DDs	85 mins.	1st (evaluation)
Expert B	Senior Manager Transaction Advisory	30 IT DDs	84 mins.	1st (evaluation)
Expert E	Consultant IT M&A	5 IT DDs	36 mins.	2nd (evaluation)
Expert I	Process Mining Specialist	>25 PM impl. projects	42 mins.	2nd (evaluation)
Coding results: We inductively analyzed the data in the 1st iteration to understand the requirements for process assessment in IT DD. In the 2nd iteration, we revealed best practices and guidelines for leveraging PM for process assessment in IT DD. In the 1st and 2nd evaluations, we evaluated the implemented IT artifact regarding efficacy, quality, and utility.				

Appendix B Embedded Publications in Original Format

Appendix B.1 P1: Turning Big Data into Value: A Literature Review on Business Value Realization from Process Mining

TURNING BIG DATA INTO VALUE: A LITERATURE REVIEW ON BUSINESS VALUE REALIZATION FROM PROCESS MINING

Research paper

Eggers, Julia, Technical University of Munich, Munich, Germany, julia.eggers@tum.de

Hein, Andreas, Technical University of Munich, Munich, Germany, andreas.hein@tum.de

Abstract

In recent years, process mining has emerged as the leading Big Data technology for business process analysis. By extracting knowledge from event logs readily available in information systems, process mining provides new ways to discover, monitor, and improve processes while being agnostic to the source system. Despite its undisputed practical relevance, we have a limited understanding of how organizations realize value potentials from applying process mining in different organizational contexts. Addressing this gap, we conduct an assessing literature review by analyzing 58 papers from the literature on process mining to synthesize the existing knowledge on business value realization from process mining. Our analysis is guided by adopting the perspective of process mining embedded within its organizational context. By analyzing the dimensions of the nomological net around process mining, we contribute to the broader research field of Big Data value realization twofold. First, we uncover which benefits organizations gain by applying process mining. Second, we analyze the organizational capabilities and practices that influence how organizations use and implement process mining. In addition, we reveal how process mining leads to business value realization. Based on these results, we suggest directions for future research on process mining in the organizational context.

Keywords: Big Data Analytics, Process Mining, IS Value Realization, Antecedents.

1 Introduction

Recent years have marked a paradigm shift in the way organizations leverage data for decision-making (Abbasi et al., 2016). Formerly, organizations used to collect data in discrete time intervals along structured paths for preconceived organizational purposes (Constantiou and Kallinikos, 2015), for instance, by monthly collecting sales data to calculate financial key performance indicators. Nowadays, organizations need to deal with vast amounts of unstructured, heterogeneous data that originate in high velocity from various sources inside and outside the firm (Jones, 2019), including social, sensor-based, or machine data (Abbasi et al., 2016). This paradigm shift is rendering established mindsets and practices for deriving knowledge from information obsolete (Kuhn, 1962), thus, coercing organizations to build new capabilities and practices for analyzing and using Big Data (Constantiou and Kallinikos, 2015). Summarized under the term Big Data Analytics (BDA), firms now strive to integrate, preprocess and analyze data in real-time to "*wring every last drop of value*" from business processes (Davenport, 2006, 2).

As organizations are always on the quest to optimize business processes continually through extracting and interpreting process data for decision-making (Constantiou and Kallinikos, 2015), process mining has received increased attention during the last decade, both from research and practice. Process mining is a BDA technique aimed at discovering, monitoring, and improving real business processes (van der Aalst, 2011). By analyzing large amounts of event data that are readily available in today's information systems, process mining depicts business processes as they are executed in an organization (van der Aalst, 2011, van der Aalst and Weijters, 2004). The German process mining start-up Celonis underpins the practical relevance with a valuation of over $1 billion (Steger, 2018) and the predicted three- to fourfold increase of the current process mining market of $160 million within the next years (Kerremans, 2019). In addition, a recent survey of 360 German companies shows that 81% have at least partially analyzed their process landscape with process mining (Reder et al., 2019). These examples illustrate how process mining – as currently the only BDA technology available for data-driven end-to-end business process analysis (van der Aalst, 2011)—is meeting organizations' increased demand to gain transparency and improve their processes to help them to adapt to quickly changing business requirements and customer expectations (Altinkemer et al., 2011).

Nevertheless, actualizing business value from BDA has proven to be difficult for firms. In a recent study, Capgemini found that only 27% of international organizations consider their BDA initiatives as "*profitable*" (Capgemini, 2016, 2). Gartner reported that international organizations abandon 60% of BDA initiatives already in the pilot phase (Heudecker and Hare, 2016). In addition, organizations that aim to adopt BDA successfully face multiple challenges. These challenges are not only technological, such as the heterogeneity and varying quality of data (Baesens et al., 2016) or the high speed of data creation (Abbasi et al., 2016), but also encompass a socio-technical dimension. The availability of vast amounts of data per se does not lead to strategic advantage and business value. It is the socio-technical process of deriving insights and acting upon these insights that create business value (Grover et al., 2018, Constantiou and Kallinikos, 2015). Still, research lacks knowledge on the underlying antecedents and processes that allow organizations to implement and use BDA IT artifacts for deriving and leveraging valuable insights (Abbasi et al., 2016). Following Benbasat and Zmud (2003), we consider it to be at the heart of the IS discipline – with its unique predisposition to study technology concerning its individual and organizational use – to investigate the BDA IT artfact within its rich socio-technical context. Thus, we are following the call of Grover et al. (2018, 392) for IS research to understand "*the mediating process and mechanisms*" that enable organizations to realize business value from BDA. Focusing on the case of process mining as a contemporary BDA technology of great practical importance, we consequently aim to answer two research questions: *(1) Which value potentials do organizations realize by implementing process mining?;* and *(2) Which socio-technical antecedents lead to realization of these value potentials?*

Towards this end, we conduct an assessing literature review, according to Leidner (2018), to systematically search and code the literature to provide a synthesis of trends or gaps. As a theoretical organizing device (Leidner, 2018), we draw on the IT artifact within its nomological net (Benbasat and Zmud, 2003). The nomological net defines the interlocking system of laws through which a phenomenon occurs (Cronbach and Meehl, 1955). Therefore, to investigate the phenomenon of interest, i.e., organizational value realization enabled by process mining, it is essential to understand the components and interrelations of the nomological net in which it occurs (Cronbach and Meehl, 1955). By contextualizing the process mining artifact within its nomological net, the assessing literature review (Leidner, 2018) synthesizes the findings of 58 empirical studies to discuss socio-technical practices and capabilities necessary for and business values enabled by process mining in organizations.

Our results contribute to research twofold. First, we contribute to the still limited understanding of what type of business values are enabled by leveraging BDA IT artifacts and what are the underlying socio-technical conditions that lead to value realization (Abbasi et al., 2016). Second, we add an organizational perspective to the research on process mining that – despite the technology's increasing practical relevance (Kerremans, 2019)—is instead focused on algorithms (Wang et al., 2012) and tool development (Turner et al., 2012) than on practical implications for organizations. These results serve as a starting point for practitioners to reflect on the purpose and necessary conditions for successfully leveraging business value from using process mining in organizations.

2 Theoretical Background

2.1 Process Mining

Process mining is rooted in constructing process models based on how business processes are executed in a specific context rather than designing them based on theoretical considerations (van der Aalst and Weijters, 2004). A business process defines how "*resources of an enterprise are used*" (Agrawal et al., 1998, 469). Because of the direct impact on organizations' performance, there has long been the question of how organizations are carrying out business processes. Agrawal et al. (1998) introduced the concept of automatically constructing process models from event logs of past executions of a process to address this problem. Since then, process mining has emerged as a technology to discover, monitor, and improve real business processes in a variety of application domains (Song and Van der Aalst, 2008, van der Aalst, 2011).

The multitudes of event data logged in information systems provide the basis for process mining (van der Aalst, 2011). The challenge for an organization is then to derive meaningful insights from these data to generate findings on process execution, discover problems of process performance, and improve the way their business operates (Song and Van der Aalst, 2008). Process mining aims to do this by leveraging event logs that comprise sequentially recorded events, where each event relates to a specific activity. These activities make up well-defined steps in a business process. Additional information, such as the person or system executing the activity, the costs related to the activity, and the timestamp of the activity, may also be available for analysis (van der Aalst, 2011).

Based on the event log, three types of process mining are possible. First, process discovery allows organizations to derive a process model that reflects the actual behavior recorded in the event log, even not knowing the process beforehand. Second, organizations can use conformance checking to compare a priori process models to the event log of the same process. Thus, firms can detect deviations of the real process from the target process (van der Aalst, 2011). Third, process enhancement helps organizations to focus on improving an existing process model based on information in the corresponding event log about the actual process. Therefore, a priori process models can be aligned to encompass certain specialties of the real process (van der Aalst, 2011).

Thus far, research on process mining has focused mainly on developing algorithms for process discovery (Ailenei et al., 2011). For example, van Dongen et al. (2009), Wang et al. (2012), and Rubin et al. (2007) provide comprehensive reviews on process mining algorithms. Furthermore, Turner et al. (2012) give an overview of process mining tools. More recently, there is a growing body of literature that recognizes the application of process mining in an organizational context. However, most of the research has been descriptive and confined to the technological facets of applying process mining in organizations. As a large share of process mining research is concerned with the implementation in a healthcare context, Rojas et al. (2016) provide an overview of the field to guide researchers when applying process mining in a healthcare context. These insights are extended by Ghasemi and Amyot (2016), analyzing the volume of research at the intersection of process mining and healthcare, and context-specific literature reviews on the applicability of process mining in oncology (Kurniati et al., 2016) and frail elderly care (Farid et al., 2019). Even though these reviews provide valuable insights on the feasibility of implementing process mining in healthcare research, the results are restricted to the technological perspective, focusing on process mining types, tools, algorithms, data sources, implementation strategies and technical challenges. Similar literature reviews can be found with a focus on process mining algorithms, tools, and methods for e-learning (Ghazal et al., 2017) and for end-to-end processes in supply chain management (Jokonowo et al., 2018). Acknowledging the diverse application scenarios for process mining in practice, the literature studies of Thiede et al. (2018) and Dakic et al. (2018) are a first step to investigate industry sectors and processes that process mining has been implemented for in empirical studies, with a focus on prevailing data sources, process mining types and tools. In conclusion, we observe a growing interest in studying the organizational application of process mining, yet, literature reviews to date have tended to focus on technological practices and challenges for applying process mining rather than on its socio-technical implications and organizational benefits. Thus, it remains unclear what socio-technical antecedents and mechanisms lead to business value realization enabled by process mining and how business values manifest.

2.2 Business Value Realization from IT

Scholars have long discussed how the implementation of IT within organizations leads to IT business value realization (Melville et al., 2004). IT business value is defined as *"the organizational performance impacts of information technology at both the intermediate process level and the organization-wide level, and comprising both efficiency impacts and competitive impacts"* (Melville et al., 2004, 287). To this end, research has mostly focused on two fields: mediating factors that impact how IT investments turn into IT-based value, such as IT-strategy alignment and organizational capabilities (Kohli and Grover, 2008) and how these IT-based values manifest (Schryen, 2010). Still, the precise mechanisms to realize business value from IT and the influence and interrelation of antecedents, such as the technological, personnel, or industry context, remain unclear (Melville et al., 2004, Schryen, 2010).

Taking into account the influence of the BDA paradigm shift, Grover et al. (2018) extend the literature on value realization from IT to encompass value realization from BDA. However, questions concerning what paths lead to value creation, how to develop appropriate BDA capabilities and practices, and how to assess the impact of BDA remain unanswered (Grover et al., 2018). These questions are of critical importance for IS research considering how BDA is changing the organizational information value chain to encompass new technologies, roles, and skills (Abbasi et al., 2016). For instance, the emergence of novel BDA IT artifacts, such as process mining analyses, requires data scientists to develop new skills in data integration, preparation, analysis, and interpretation to support real-time data-driven insights (Abbasi et al., 2016). Such insights from process mining result in diverse business values, ranging from shortening production times through transparency on bottlenecks (Lee et al., 2014) to improved customer satisfaction through enhanced service quality by uncovering neglected but essential process steps in customer care (Edgington et al., 2010). Those examples illustrate how BDA is impacting and impacted by the embedded organizational context.

To understand the interplay between the IT artifact and its organizational context, Benbasat and Zmud (2003) call for IS research to study the IT artifact within its immediate nomological net. The immediate nomological net comprises (1) the IT artifact, which is defined as "*the application of IT to enable or support some task(s) embedded within a structure(s) that itself is embedded within a context(s)."* This rich organizational context manifests itself in (2) organizational capabilities and practices that comprise "*the managerial, methodological and technological capabilities as well as the managerial, methodological, and operational practices involved in planning, designing, constructing, and implementing IT artifacts*" (Benbasat and Zmud, 2003, 186). Resulting from (3) its use in the organizational context, the IT artifact (4) impacts "*the humans who directly (and indirectly) interact with them, structures and contexts within which they are embedded, and associated collectives (groups, work units, organizations)*" (Benbasat and Zmud, 2003, 186). By investigating the IT artifact within its immediate nomological net, IS research strives to understand the socio-technical antecedents and processes that enable organizations to implement IT and realize value from its use (Benbasat and Zmud, 2003).

3 Design of the Literature Review

We conducted an assessing literature review, according to Leidner (2018). We chose this type of literature review as it is suitable for synthesizing current trends and gaps in a research stream by systematically coding the extant literature according to a pre-defined theoretical framework (Leidner, 2018). This approach enables us to rigorously identify what is known and unknown about the antecedents and impacts of process mining usage in organizational settings through contextualizing process mining as an IT artifact within its immediate nomological net (Benbasat and Zmud, 2003).

3.1 Sampling

Following the systematic literature search process of Webster and Watson (2002), we screened relevant outlets and looked for publications that (a) focus on organizational usage of process mining and (b) include an empirical study on implementing the use case. Subsequently, we coded the studies based on the dimensions of the nomological net surrounding process mining. We used the leading Information Systems (IS) journals included in the Association for Information Systems (AIS) Senior Scholars' Basket of A-rated IS journals (Association for Information Systems, 2011) as the starting point for finding relevant literature. We expected the publication of relevant articles on process mining in an organizational context in these leading IS journals. To further the organizational perspective on process mining, we also included the Financial Times 50 (FT50) journal list (Ormans, 2016). To enrich the data set with contemporary studies, we included the proceedings of the International Conference on Information Systems (ICIS) and the European Conference on Information Systems (ECIS) as the top IS conferences. Since process mining has its roots in computer science research, we included the top five journals from the AIS special interest group on Decision Support and Analytics as we expected them to add to the technical perspective on process mining. To deepen the technical perspective, we included IEEE Access, IEEE Transactions on Services Computing, IEEE Transactions on Knowledge and Data Engineering, and the Communications of the ACM, as these outlets publish research on process mining regularly. Finally, we included the proceedings of Business Process Management Workshops (BPMW) and the Business Process Management Journal since process mining is deeply related to business process management research.

		Initial search		FW/BW
	Outlet	Hits	Selected	Selected
Senior scholars' basket and FT 50	European Journal of Information Systems	1	0	-
	Information Systems Research	1	0	-
	MIS Quarterly	3	0	-
	INFORMS Journal on Computing	1	0	-
	The Accounting Review	2	1	-
	Organization Science	2	0	-
	Production and Operations Management	1	0	-
AIS SIG	Decision Support Systems	16	4	-
	Expert Systems with Applications	26	8	-
	Information Systems Frontiers	4	2	-
AIS conf.	ICIS	26	0	-
	ECIS	52	4	-
Process mining- relevant conferences and journals	BPMW	389	7	-
	Communications of the ACM	1	0	-
	IEEE Transactions on Knowledge and Data Engineering	9	0	-
	IEEE Access	15	2	-
	IEEE Transactions on Services Computing	19	1	-
	Business Process Management Journal	32	1	-
Other	Other journals	100	15	-
	Other journals	-	-	12
	Other conferences	-	-	1
		700	45	13

Table 1. Summary of the literature search process.

3.2 Data Collection

As a first step, we deployed a keyword search for "process mining" in title, abstract, and keywords without temporal limitation on Scopus, Web of Science, AIS e-Library and IEEExplore, restricting the search to the previously identified relevant outlets. The initial search revealed 700 hits. Next, we analyzed the articles regarding their title and abstract to reveal their importance for understanding value realization enabled by process mining. We only included articles with an empirical study where the authors investigated the application of process mining for an organizational use case. This process yielded 45 articles, which we supplemented through a forward and backward search (Webster and

Watson, 2002). The backward search resulted in an additional six articles, and the forward search resulted in an additional seven articles. In sum, the final set comprised 58 research articles published between 2005 and 2019 (see Table 1). We attached the complete list of included articles in the reference section and marked them with an asterisk.

3.3 Analysis

Following Leidner (2018), we use the nomological net surrounding process mining (Benbasat and Zmud, 2003) as a theoretical framework to guide the coding process. To conduct the literature coding, we followed a grounded theory coding process (Glaser and Strauss, 1967). This approach comprises open coding of first-order concepts from the literature that describe the phenomenon of interest, i.e., value realization enabled by process mining in organizations. Then, we formed second-order constructs in the process of axial coding to establish relationships between the codes. In the last step, we conducted selective coding to aggregate dimensions that describe relating second-order constructs (Gioia et al., 2013). As we contextualize organizations' use of process mining as an IT artifact within its nomological net, we followed an abductive approach. In this approach, we used the dimensions of the nomological net as selective codes and conducted the open and axial coding inductively based on the selected papers. Starting with open coding, we used a line-by-line coding approach to extract quotes that relate to the antecedents for and value generation enabled by process mining. We then categorized the resulting 169 first-order codes into 47 second-order themes that comprise relationships (Gioia et al., 2013). For instance, we discovered that through process mining firms obtain, among others, *transparency on frequent process flows*, *transparency on anomalous process flows*, and *transparency on employee interaction*. We then summarized these first-order concepts under the second-order theme *transparency*. In the last step, we matched the derived 47 second-order themes to the four dimensions of the nomological net that served as aggregate dimensions. In case a second-order theme could not be related to one dimension, we excluded it from further analysis to strengthen our focus on the nomological net. For example, we abandoned the theme *industry* as we discovered that as part of the organization's technological capabilities, the source system providing the data for the process mining analysis is mirroring the process and the respective industry. Similarly, we dropped the theme *challenges* as these turned out to manifest in the nomological net as part of the process mining artifact and technological capabilities of the firm. In sum, we obtained four aggregate dimensions that reflect the contextualized nomological net for process mining as an IT artifact implemented and used by organizations.

4 Results

We describe the results from our literature review along the dimensions of the nomological net (Benbasat and Zmud, 2003) surrounding the process mining artifact. The (1) process mining IT artifact is (2) used by organizations and embedded within an organizational context that comprises (3) specific organizational capabilities and practices that are necessary to design and implement the process mining analysis, so the organization can (4) realize business value potentials from its use (see Figure 1). As our analysis focuses on explicating the dimensions of the nomological net around process mining, the arrows in Figure 1 show exemplary relationships that we further elaborate on as avenues for future research.

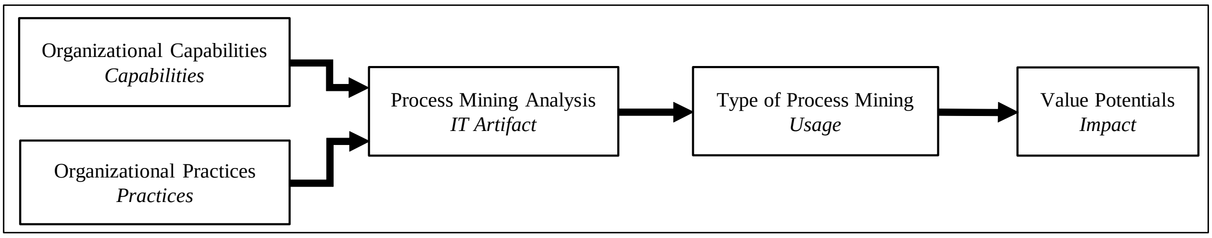

Figure 1. Process mining as IT artifact within its nomological net (based on Benbasat and Zmud 2003).

4.1 Process Mining as an IT Artifact

Governing the evolving lifecycle of the process mining artifact is a challenge that researchers are addressing with various implementation procedures, such as the L* lifecycle model (van der Aalst et al., 2011) or the Process Diagnostics method (Bozkaya et al., 2009). These procedures support firms in executing the different stages of a process mining project, from understanding the goal of the analyses over extracting and preparing data to create process models and interpreting the results (van der Aalst et al., 2011).

Such implementation procedures revolve around the process mining analysis as an IT artifact at the center of the implementation project. We observe three specific characteristics that distinguish process mining from other IT implementations. First, the plethora of available mining algorithms urges organizations to familiarize themselves with available methods and select the appropriate algorithm regarding the data quality and process analysis goals (van der Aalst, 2011). Widely adopted algorithms (Erdogan and Tarhan, 2018, De Weerdt et al., 2012b), are complemented by highly specialized algorithms that scholars can adapt to a specific problem context (Breuker et al., 2016).

Second, the results indicate that the selection of a suitable algorithm relates tightly to the underlying data quality. The impact and success of process mining in an organization depend on the availability and quality of event data that represent a process flow (Knoll et al., 2019). These data may be distributed in different formats and granularity intra-organizationally across various systems or even inter-organizationally across different firms (Quaglini, 2008). Obtaining, pre-processing, and merging these data, especially regarding incomplete (Leyer and Moormann, 2015) or outlier-prone event logs (Măruşter and van Beest, 2009), poses hurdles that organizations need to overcome to implement valuable process mining artifacts (van der Aalst et al., 2011).

Third, valuable process mining artifacts also depend on the design of the process mining analysis. As process mining can display process flows as maps, organizations need to decide on the perspective and level of granularity that such a process map should provide (Partington et al., 2015). While an auditor may be interested in highly detailed visualizations of individual process flows to detect fraudulent behavior (Jans et al., 2014, Baader and Krcmar, 2018), users from management-level may rather be intrigued by the aggregating analysis of costs related to specific process steps (Ceglowski et al., 2005). This example illustrates that the design of the process mining analysis is strongly influenced by the intended usage of the IT artifact.

4.2 Usage of the Process Mining Artifact

The majority of research focuses on how organizations **discover as-is business processes** (Ho et al., 2009, De Weerdt et al., 2012a), either by discovering process models (Baader and Krcmar, 2018, De Leoni et al., 2016) or interaction models (Alvarez et al., 2018, Stuit and Wortmann, 2012). With regards to the chosen mining algorithm, the discovered process model can display different levels of complexity, from a static view of the behavior found in the event log to an analysis of more or less frequent paths (Jans et al., 2014, van der Aalst, 2011). This extension of process discovery allows for the **analysis of different variants** of the same process. Organizations can draw on these insights to reflect on the complexity and diversity of business processes. A typical use of process discovery is the application in hospitals where, despite a highly regulated environment, patients with diverse needs require individual treatment flows (Zhou and Piramuthu, 2010).

The understanding of actual process flows furthered by using **conformance checking** to detect deviations from standard process models (Bozkaya et al., 2009, He et al., 2019, Li et al., 2011). Once deviations are known and assessed, organizations can leverage this knowledge to enhance the existing process models to be more appropriate and comprehensive, a process mining technique known as **process enhancement** (Li et al., 2011).

As process mining creates transparency on process flows, organizations use it to **assess the performance** of business processes. Process performance is typically measured in throughput times, which is reflected in the time required to perform a process (Bozkaya et al., 2009, Rebuge and Ferreira, 2012), the number of bottlenecks such as activities delaying the process (De Leoni et al., 2016) or process loops in the form of repeated execution of activity patterns (van der Aalst et al., 2007, Măruşter and van Beest, 2009). To gain more accurate results, scholars started to combine process mining and data mining techniques, such as decision and regression trees, to derive predictions of how particular process characteristics will influence the process outcome (De Leoni et al., 2016). These **predictions** can inform measures to intervene on process flows that will probably lead to reduced quality output.

4.3 Organizational Capabilities and Practices

Successfully implementing process mining projects in an organizational context implies organizational capabilities and practices as antecedents to value realization. Based on the literature, we found only one study focused on organizational success factors for implementing process mining, derived from the literature on process modeling (Mans et al., 2013a).

First, **organizational capabilities** are a crucial requirement for process mining project success, which are reflected in the organizational context as well as the data and system context. The organizational context comprises general project-related factors, such as the capability of the company's senior management to support the process mining initiative and the availability of resources to execute the project (Mans et al., 2013a). Besides, we also observe the relevance of process mining-specific factors that extend to the data and system context. The availability and quality of raw data and the constructed event logs are critical antecedents to successful process mining (Mans et al., 2013a, Knoll et al., 2019). Depending on the industry and process under consideration, different information systems serve as a source for the event data. That is the reason we observe a high fragmentation of source systems in the literature. With a clear emphasis on studies of clinical pathways in the healthcare sector (36%), the dominant source systems are Hospital Information Systems and the Electronic Health Record (combined 21%) that provide structured information on patient treatments and medical workflows (Alvarez et al., 2018, Rojas and Capurro, 2019). As 22% of the studies investigate core business processes, such as Purchase-to-Pay (Baader and Krcmar, 2018, van der Aalst et al., 2007) or Order-to-Cash (Fleig et al., 2018, Măruşter and van Beest, 2009), Enterprise Resource Planning systems and Workflow Management Systems provide a frequent source of rich event data. Both systems usually yield highly structured and detailed event data (van der Aalst et al., 2011) that can be pre-processed rather effortlessly, e.g., through standardized SQL scripts (Fleig et al., 2018). In contrast, process mining has also been applied to specialized systems (Brunk et al., 2018, Zerbino et al., 2018) or to manually collected data, for instance, observer-based data of surgical procedures (Lira et al., 2019). These data, however, are often ambiguous and incomplete and thus require extensive expert knowledge for pre-processing so that chronological, concise event logs can be produced (He et al., 2019).

Second, **organizational practices** need to be in place to foster the implementation and usage of process mining. The process mining implementation requires a structured procedure and project management and the availability of analytical expertise to prepare and conduct the process mining analysis (Roldán et al., 2018, Mans et al., 2013a). This procedure includes strategies to collect event data, the careful selection of suitable process mining algorithms given the problem at hand (Mans et al., 2013a), and the focus on relevant areas of analysis (Partington et al., 2015). Furthermore, the discussion with project stakeholders and process owners, which we found to be a crucial practice for realizing meaningful process mining projects, influences this process. The main goal of discussion between stakeholders is to validate the quality of raw data and the interpretation of analysis results (Alvarez et al., 2018, Zerbino et al., 2018), which encompasses the distinction between wanted and unwanted deviating behavior (Bozkaya et al., 2009, Helbig et al., 2016) and interpreting root causes for process variances (Fernández-Llatas et al., 2013, Wang et al., 2014) and the estimation of severity in case of non-conformance to specific process standards (Zerbino et al., 2018). Thereby, the discourse of stakeholders enables faster identification of meaningful results (van der Aalst et al., 2007). How the analysis results are presented and communicated to the project stakeholders shapes the way the following discussion and use of the results unfolds (Cho et al., 2017). Presenting the resulting process models in an interactive rather than static or descriptive manner may ease the interpretation for organizational stakeholders (Bozkaya et al., 2009).

4.4 Organizational Impact

With a research focus on the control-flow of processes, 74% of studies focus on the **transparency** of process flows as a significant value of process mining. Process mining allows uncovering the execution of processes in a specific context and can yield insights on the most frequent process flows as well as on infrequent or anomalous flows. Drawing on this characteristic, firms can create a model of how a particular process is executed, which can then be used to uncover anomalous, fraudulent executions that lack specific process steps (Jans et al., 2014). Those insights serve as input for the auditor to detect fraud comprehensively much earlier in the audit compared to traditional techniques that focus on random tests of internal control mechanisms (Jans et al., 2011). Process mining-enabled transparency also extends to the organizational perspective, as it generates transparency on organizational structures that manifest in employee roles and allocation. Organizations use process mining to construct models representing the interaction of employees, giving insights on how employees are allocated and how they collaborate. As a result, firms can identify employees suffering from high workload (Pika et al., 2017) or detect inefficient interaction patterns, for example, in emergency departments where efficient collaboration is vital (Alvarez et al., 2018, Mans et al., 2008). Process mining also enables transparency in customer behavior. Shopping malls use this transparency to discover customer paths in their malls based on a Bluetooth-based positioning system (Dogan et al., 2019), or healthcare institutions get insights of sudden changes in behavioral patterns of seniors at risk of suffering from dementia episodes (Fernández-Llatas et al., 2013).

Based on process mining-induced transparency, the studies show a clear tendency to measure process **performance** and to increase process **efficiency**. For example, process mining is used to find root causes for long cycle times in service processes in the financial industry, so that after identifying bottlenecks, alternative, faster workflows can be proposed, which leads to increased efficiency that can be estimated through simulation models (Leyer and Moormann, 2015). Analyzing the suppliers' lead time in a production process, Lau et al. (2009) enrich these performance data with additional production information and derive association rules on how these parameters influence the product quality. The combination of process mining with diverse analysis techniques, such as association rule mining (Lee et al., 2014), simulation models (Cho et al., 2019), or clustering techniques (Lee et al., 2013), is notable. Combining analysis techniques allows expanding the capabilities of process mining to not only analyze the process and its immediate context but also to correlate different process characteristics (De Leoni et al., 2016) and estimate their impact on, among others, product quality (Lau et al., 2009), human behavior (Brunk et al., 2018) or customer satisfaction (Ho et al., 2009).

Enterprises must ensure the **conformance** of their processes to regulatory requirements and internal workflow standards. Conformance is due to both an increase in external, regulatory requirements, such as the Sarbanes-Oxley Act (SOX), and the need for organizations to align their processes to support quickly changing business requirements optimally (van der Aalst, 2011). To this end, process mining allows the analysis of conformance of a real process with the desired process model to detect any deviations (Rebuge and Ferreira, 2012). This type of process mining also enables companies to generate automated recommendations on a suitable standard process model to reduce the overall costs of **standardization** (Fleig et al., 2018).

Process mining allows for a fact-based implementation and **monitoring of organizational change**, facilitated by the ability to gain transparency on process flows and measure process performance. To this end, scholars employ process mining to validate the effects of business process reengineering projects, yielding results on time savings and cost increases related to different reengineering measures

(Cho et al., 2017). **Forecasting** the effects of organizational changes by process mining allows decision-makers to make more informed decisions on change projects while decreasing the effort for data generation and analysis (Alvarez et al., 2018, Roldán et al., 2018).

5 Discussion, Limitation, and Conclusion

It is inherent to the IS discipline to deepen the understanding of how elements of the nomological net are interconnected, to understand how IT artifacts are constructed, implemented, and used, and how they impact the context they are embedded in (Benbasat and Zmud, 2003). Building on the dimensions around the process mining artifact in organizations that resulted from our literature review, we now turn to relationships between the elements to illustrate fruitful areas for future research.

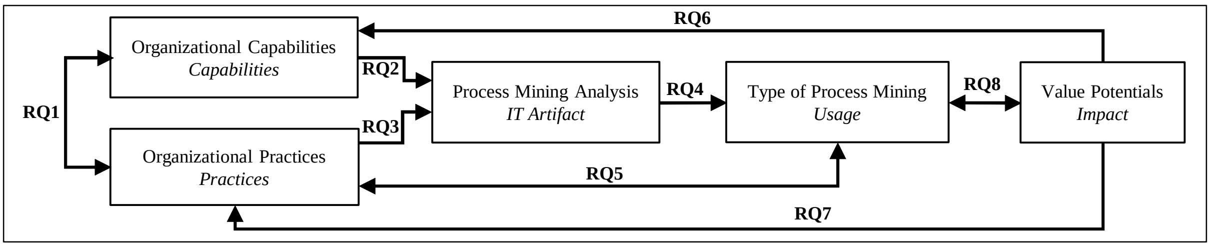

Figure 2. Potential research questions related to process mining within its nomological net.

5.1 Developing Antecedents for Process Mining

Even though the realization of value potentials enabled by process mining requires specific organizational capabilities and practices (Mans et al., 2013a), there is sparse knowledge of **how these antecedents are developed**. First, we turn to the **interplay of organizational capabilities and practices** as antecedents for implementing and using process mining. We expect **organizational practices** to influence the development of technological capabilities for process mining. An example is the influence of IT governance practices on the provision of data necessary for process mining. IT governance provides rules that imply "*which department makes what IT decisions*" (Tiwana and Kim, 2015, 656), including decisions on what, for example, structured and unstructured, and how, for example, centralized or decentralized, data will be stored (Weill and Ross, 2004). Storing and handling data in a centralized or decentralized approach defines whether processes can interlink business units end-to-end in a standardized way or are highly diversified for each business unit (Weill and Ross, 2004). We call for researchers to investigate how managerial practices, such as IT governance mechanisms, are facilitating or hindering the exploitation of process mining, thus, contributing to the debate on the interplay of BDA and organizational culture (Abbasi et al., 2016).

In turn, also organizational practices to implement and use process mining will vary depending on the **organization's capabilities** in data storage and provision. Applying process mining to highly regulated production processes may require different practices in data pre-processing, analysis design, and usage than the implementation for flexible, human-centric processes. While production processes usually provide large amounts of detailed, structured log data (Mans et al., 2013a), human-centric, behavioral processes are often not digitally tracked, evolve and, in contrast to most business processes, do not provide clear precedence among activities (Fernández-Llatas et al., 2013). Organizations are then challenged to develop data collection and analysis practices to cope with incomplete and unstructured data sets. These newly established practices can be iterative and agile as an incremental identification, and analysis of distributed process data in collaboration with diverse stakeholders becomes necessary (Pika et al., 2017). In addition, processes with critical effects, for example, on human lives, require different practices in data analysis and change implementation. Analyzing and optimizing the performance of hospital emergency room episodes has a direct impact on human lives (Rojas et al., 2019), thus requiring a careful ex-ante validation of patient data and ex-post discussion of analysis results. In contrast, the continuous monitoring to improve production processes requires a thorough ex-ante discussion with stakeholders to develop a shared understanding of process characteristics relevant for long-term analysis (Lee et al., 2014). In conclusion, we encourage researchers to investigate these interdependencies to shed light on how firms need to adapt their organizational practices and technological capabilities when implementing BDA. We therefore pose ***RQ1: What are reciprocal effects between organizational practices and technological capabilities as antecedents for process mining?***

5.2 Implementing Process Mining

Even though firms draw on organizational practices and capabilities to **implement the process mining artifact**, to the best of our knowledge, it is not fully understood how these antecedents affect the design and implementation of process mining in organizations. Most studies in the process mining literature examine the design and implementation of process mining artifacts from the viewpoint of the researcher who seeks to adapt and implement the technology for a novel use case. Despite valuable insights on opportunities for process mining resulting from this approach, we consider it crucial to acknowledge the perspective of organizational users, who are ultimately shaping the design and usage of process mining based on their expertise (Mans et al., 2013a). Different degrees of **analytical and decision-making capabilities** influence how users derive and act upon insights from process mining. Certain features, such as an initial process discovery enabled by plugin modules in process mining tools (Bozkaya et al., 2009), are easy to implement and understand for users with limited analytical expertise. Other analysis types, such as a process model validation and enhancement, potentially deliver more profound insights but require expert knowledge in implementation and interpretation (Roldán et al., 2018). This ambiguity raises the question of who needs what information in which format at what time to make decisions. A senior manager may be interested in a high-level analysis of resource allocation and performance to estimate overall improvement potentials (Fleig et al., 2018), while a process owner may want to analyze production process performance depending on specific machine settings or process operators (Ho et al., 2009). We, therefore, encourage scholars to focus on how these capabilities impact the design and usage of process mining artifacts that enable different types and levels of analysis and how these lead to different business values: ***RQ2: How are users' analytical and decision-making capabilities impacting the design and use of process mining artifacts?***

While it is essential to address questions about capabilities on an individual level, it is equally important to acknowledge the group level. Creating a shared mindset among employees and establishing **collaborative practices** is essential for firms striving to successfully leverage BDA (Dremel et al., 2017). The importance of such practices becomes clear when thinking of the technical and social demands that process mining poses for an organization. On the one hand, process data may be distributed in varying formats and quality across several departments and IT systems (Ho et al., 2009). On the other hand, diverse stakeholders – ranging from IT specialists to process owners and operators to data scientists – have distributed knowledge on technologies and processes that is critical to the success of process mining (Zerbino et al., 2018). While we expect collaboration across departments, roles, and systems to positively influence the implementation and usage of process mining artifacts in organizations, we consider it necessary to investigate what collaborative practices have an exceptionally high impact on process mining implementation and usage and how those can be established: ***RQ3: What collaboration practices influence the implementation and usage of process mining artifacts?***

5.3 Using Process Mining

How a firm **uses process mining** depends on one hand on the process mining artifact itself. Foremost, the **design and implementation of the process mining artifact** will impact how users adopt the technology. Users' intention to employ the technology will likely increase when their needs and expectations towards the technology are met (Venkatesh et al., 2003). Technology acceptance has long been studied in IS research, leading to a variety of models that have also been adapted to the BDA context (Verma et al., 2018, Gunasekaran et al., 2017). In the realm of BDA, factors such as information quality and quality of information processing become salient for technology acceptance (Verma et al., 2018), as the overarching goal of system usage shifts to exploring data and deriving knowledge (Marchand and Peppard, 2013). We expect these BDA-specific factors to be crucial for process mining. However, research has not addressed if existing BDA technology acceptance models hold for process mining and whether and which characteristics of the process mining artifact differentiate it from other BDA technologies. We, therefore, propose ***RQ4: How are characteristics of the process mining artifact impacting the intention to use the technology?***

On the other hand, the use of process mining is influenced by **organizational practices**. Process mining increases transparency on the organization's business processes. However, the process of collecting and preparing the necessary data basis may often remain invisible to the broader public as it is executed automatically in the underlying IS (Jans et al., 2014). Richards and King (2013) sound a cautionary note on this transparency paradox and call for BDA leaders to acknowledge this ambiguity by developing mechanisms that inform the people impacted by BDA on how data are collected and how insights are derived (Richards and King, 2013). Thus, we encourage researchers to remember that process mining is a powerful tool with the potential to analyze the workflows of individual human beings in almost unlimited detail. With this power, **ethical considerations** on process mining become paramount. We see the need to extend the currently technologically-driven research on process mining also to include ethical questions on collecting, preparing, and analyzing process data for individuals and organizations that use and are influenced by process mining, as summarized in ***RQ5: What are the reciprocal effects between ethical considerations and the usage of process mining artifacts?***

5.4 Realizing Value from Process Mining

Our results suggest that the organizational use of process mining enables a multitude of value potentials, ranging from workload transparency to improved process performance to monitoring organizational change initiatives. However, these outcomes are not an end in themselves, but in turn, have reinforcing effects on future value realization from process mining. First, we propose that realized value potentials have an amplifying impact on the **development of technological capabilities**. An example is the organization's capability to provide reliable data to reconstruct event logs. There is consensus that reliable data is the most crucial antecedent to the meaningful implementation of process mining (van der Aalst and Weijters, 2004). However, research shows that data availability is an ongoing challenge in process mining since firms struggle to obtain and pre-process suitable data (Kerremans, 2019, van der Aalst et al., 2011). One way to improve data quality may be the use of initial process mining analysis to discover that essential processes are not tracked in the IS (Jans et al., 2014). This approach may lead to changes in the underlying IS or the development of new tracking capabilities, such as implementing RFID (Lee et al., 2014), to enable more detailed process mining analyses that potentially lead to deeper insights. Even though implementing process mining may face technological difficulties in the early stages, reinforcing mechanisms make long-term value potentials transparent. Hence, we aim to contribute to the debate on BDA value creation mechanisms, particularly considering data availability issues (Abbasi et al., 2016, Grover et al., 2018) through ***RQ6: How do realized value potentials influence the enhancement of technological antecedents for process mining?***

Second, we expect values realized from process mining to impact the further **development of organizational** practices, for instance, process-oriented business practices. Research has long acknowledged that in today's fierce competition, organizations are coerced to shift their focus from governing business functions to holistic design and governance practices of end-to-end business processes (Kim et al., 2011). Even though organizational process-orientation is known to lead to benefits such as improvement of customer satisfaction and financial performance (Kohlbacher, 2010), organizations face challenges during implementation in practice. Process-orientation imposes high demands on organizations to govern such end-to-end processes (Willaert et al., 2007) and to implement desired process changes in practice (Jurisch et al., 2016). We expect process mining to facilitate the establishment of process-oriented organizational practices. One reason is that process mining has been reported to foster transparency on end-to-end processes (Özdağoğlu et al., 2019) and facilitate monitoring of business process reengineering projects (Cho et al., 2017) which are fundamentals of process-oriented organizational practices. The other reason is that obtaining and acting upon results from process mining is also known to enhance the "*process-oriented thinking"* of employees (Fleig et al., 2018, 240) by making them aware of how business processes are executed and interlinked in reality. Consequently, we encourage scholars to further deepen our understanding of how process mining is acting as facilitator for process-oriented practices that acts as enabler for value realization: ***RQ7: How do realized value potentials influence the establishment of process-oriented organizational practices?***

Third, we propose that the use of process mining will impact the **transition towards data-driven decision-making processes**. Consider, for example, that workflows that were once considered optimally designed and flawless now become transparent in their actual execution and performance through process mining (Fleig et al., 2018). This means that processes and behaviors that used to be hidden now become transparent through data-driven analysis, and executives can take actions based on these objective insights, which opens up new avenues for value creation. However, this newly introduced data-driven transparency replaces previous decision processes that were based on expert assessments or personal hunches. An arising tension between data-driven implications of the analysis and the intuition-based recommendations of the experts is the result. This tension fuels some of the most urgent questions of BDA research, i.e., the way organizations "*transform from an intuition-based decision-making culture to a data-driven decision-making culture*" and how to establish the ideal balance between data and intuition (Abbasi et al., 2016, xiii). We, therefore, encourage future longitudinal studies to shed light on how novel analytics technologies are transforming decision-making culture in organizations, as summarized in ***RQ8: How is the organizational usage of process mining impacting the transition from intuition-based decision-making to data-driven decision-making?***

Theme	Research Question
Developing Antecedents	**RQ1:** What are reciprocal effects between organizational practices and technological capabilities as antecedents for process mining?
Implementing Process Mining	**RQ2:** How are users' analytical and decision-making capabilities impacting the design and use of process mining artifacts? **RQ3:** What collaboration practices influence the implementation and usage of process mining artifacts?
Using Process Mining	**RQ4:** How are characteristics of the process mining artifact impacting the intention to use the technology? **RQ5:** What are the reciprocal effects between ethical considerations and the usage of process mining artifacts?
Realizing Value	**RQ6:** How do realized value potentials influence the enhancement of technological antecedents for process mining? **RQ7:** How do realized value potentials influence the establishment of process-oriented organizational practices? **RQ8:** How is the organizational usage of process mining impacting the transition from intuition-based decision-making to data-driven decision-making?

Table 2. Questions to guide future research on process mining.

Table 2 summarizes the questions that we consider fruitful avenues for future research on process mining in its socio-technical context. However, we recognize that our review is subject to several **limitations**. First, by adopting the method of an assessing literature review (Leidner, 2018), we drew on the theory of the IT artifact in its nomological net (Benbasat and Zmud, 2003) to guide our analysis. Even though we consider this a valuable framework close to the core of the IS discipline to study the construction process and impact of IT in organizations, other more specific theoretical frameworks, such as the BDA value creation framework (Grover et al., 2018), may inform different insights outside the nomological net around process mining. Second, we ground our analysis in the results of 58 empirical studies on the organizational use of process mining that span a diverse field of application scenarios. Even though this allowed us to derive various antecedents for and value potentials enabled by process mining and to identify open questions on the underlying mechanisms that still need to be answered, we acknowledge the need for further expanding our understanding of hitherto unknown values and mechanisms in practice by, for example, acquiring longitudinal data through multiple case studies.

As organizations are challenged to adapt their processes to quickly changing business requirements, the potential of Big Data-driven insights enabled by process mining becomes increasingly valuable. However, practitioners still fail to leverage the potential benefits of process mining. Toward this end, this study puts process mining in its organizational context represented by the nomological net. This broadens our understanding of the interplay between process mining and the realization of value in organizations. Furthermore, we depict a research agenda of how organizations develop the antecedents necessary to implement process mining and how lasting business value can be created.

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(* result of the literature review process)

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Appendix B.2 P2: No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness

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RESEARCH PAPER

No Longer Out of Sight, No Longer Out of Mind? How Organizations Engage with Process Mining-Induced Transparency to Achieve Increased Process Awareness

Julia Eggers · Andreas Hein · Markus Böhm · Helmut Krcmar

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Abstract In recent years, process mining has emerged as the leading big data technology for business process analysis. By extracting knowledge from event logs in information systems, process mining provides unprecedented transparency of business processes while being independent of the source system. However, despite its practical relevance, there is still a limited understanding of how organizations act upon the pervasive transparency created by process mining and how they leverage it to benefit from increased process awareness. Addressing this gap, this study conducts a multiple case study to explore how four organizations achieved increased process awareness by using process mining. Drawing on data from 24 semi-structured interviews and archival sources, this study reveals seven sociotechnical mechanisms based on process mining that enable organizations to create either standardized or shared awareness of sub-processes, end-to-end processes, and the firm's process landscape. Thereby, this study contributes to research on business process management by revealing how process mining facilitates mechanisms that serve as a new, data-driven way of creating process awareness. In addition, the findings indicate that these mechanisms are influenced by the governance approach chosen to conduct process mining, i.e., a top-down or bottom-up driven implementation approach. Last, this study also points to the importance of balancing the social complications of increased process transparency and awareness. These results serve as a valuable starting point for practitioners to reflect on measures to increase organizational process awareness through process mining.

Keywords Big data analytics · Process mining · Sociotechnical mechanisms · Process awareness · Process orientation · Business process management

1 Introduction

Organizations nowadays have an abundance of data at their hands, originating from various sources inside and outside the firm (Jones 2019), that provide them with novel capabilities for analyzing internal and inter-firm processes. Taking advantage of the vast amount of data, process mining has received increased attention over the last decade from both researchers and practitioners. Process mining is a big data analytics (BDA) technique for discovering business processes, checking process conformance, and enhancing process models (van der Aalst 2016). By analyzing large amounts of event data readily available in contemporary information systems, process mining reveals business processes as they are executed (van der Aalst 2016), generates process transparency, and thus enables firms to rapidly adapt to quickly changing business requirements (vom Brocke and Mendling 2018). The success of German process mining start-up Celonis—valuated at $ 11.1 billion as of June 2021 (Konrad 2021)—is indicative of process mining's practical relevance, and a predicted three- to four-fold increase in the current $160 million process mining market suggests its continued importance (Kerremans 2019).

Process mining is expected to facilitate process optimization by creating unprecedented transparency of business processes (van der Aalst 2016). Formerly, firms relied

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J. Eggers (✉) · A. Hein · M. Böhm · H. Krcmar
Krcmar Lab, Department of Informatics, Technical University of Munich, Boltzmannstraße 3, 85748 Garching, Germany
e-mail: julia.eggers@tum.de

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on manual process modeling and the heterogeneous, subjective process knowledge of individuals scattered across the organization to create process transparency (Dumas et al. 2018). Today, process mining creates transparency of a firm's as-is process variations, including less known and less frequent processes, as long as they are recorded in the firm's IT systems (Jans et al. 2014). Thus, process mining constitutes a turning point for many organizations as they become aware of their process variety for the first time (Davenport 2020).

While process awareness is considered the starting point for organizations to shift their focus towards comprehensive process management across organizational silos (Kohlbacher 2010), achieving data-driven process awareness based on process mining has proven difficult for firms. A recent study from Germany reported that even though 80% of the 360 firms surveyed use process mining with the goal of achieving process transparency and awareness, they face challenges in realizing the expected benefits, for example, due to resistance to transparency and an insufficient process-oriented mode of thinking in the workforce (Reder et al. 2019). This indicates that even though process mining provides the technological potential to create unprecedented process transparency, process awareness does not automatically follow from its use. Instead, organizations still struggle to employ the mechanisms to leverage transparency for process awareness. This observation resonates with recent research that highlights the need to understand how organizations act upon the pervasive transparency created through process mining (Grisold et al. 2020; Mendling et al. 2020) and how they leverage the transparency to benefit from increased process awareness (Eggers and Hein 2020). As process awareness consists of a multi-layered construct that requires a firm to develop a shared process language and understanding (Christiansson and Rentzhog 2019), achieving it with the help of technology should not only be investigated as a merely technical question but instead as a socio-technological phenomenon (Sarker et al. 2019). It is a phenomenon that consists of a technical component, such as the process mining tool, and the social component, such as the organization's individuals and collectives and their relationships and interactions (Sarker et al. 2019) that are inextricably interwoven while achieving technology-enabled process awareness. Nevertheless, thus far, research on process mining has mainly focused on advancing the technological basis (Grisold et al. 2020), while its sociotechnical implications remain largely unknown. We, therefore, set out to study process mining in its sociotechnical context to shed light on how firms engage with the process transparency created from process mining to achieve increased process awareness. Thus, we address the following research question:

RQ: How do organizations engage with the process transparency created by process mining to increase organizational process awareness?

To this end, we conduct an exploratory multiple case study to study process mining as a contemporary phenomenon within its real-world context (Eisenhardt 1989). We choose a qualitative approach as we consider the organizational context (Eisenhardt 1989) in which process mining is applied, such as the industry, the company size, and the process analyzed, to be important for understanding the mechanisms that lead to process awareness. Thus, we study four organizations of different sizes and industry settings that focus on different processes. Drawing on data from 24 semi-structured interviews and archival sources, we reveal seven mechanisms that enable organizations to create process awareness from process mining. Surprisingly, our findings indicate that these mechanisms depend on the governance approach chosen to conduct process mining, i.e., a top-down or bottom-up driven implementation approach.

Our results contribute to research threefold. First, our study contributes to research on business process management (BPM) that highlights the challenges of achieving process awareness (Christiansson and Rentzhog 2019; Dumas et al. 2018) by revealing process mining-enabled mechanisms as a new, data-driven way of creating process awareness. Second, our research sheds light on the hitherto unknown implications of the governance structure of process mining projects (Mendling et al. 2020; vom Brocke et al. 2014) for the mechanisms that allow firms to create and leverage process transparency. Third, our study also points towards the importance of taking measures to balance the social complications of increased transparency (Richards and King 2013). These results serve as a starting point for practitioners to reflect on measures to increase organizational process awareness through process mining.

2 Theoretical Background

2.1 Process Mining

Based on the multitudes of event data logged in information systems, organizations can derive meaningful insights into process execution, discover process performance problems, and improve the way their business operates (van der Aalst 2016). To this end, process mining leverages event logs that comprise sequentially recorded events in which each event relates to a specific activity as a step in a business process. Additional information, such as the person executing the activity, the costs related to the activity, and the activity's timestamp, may also be available for analysis (van der Aalst 2016). In summary, firms can use process mining to discover process models without prior knowledge of a process, to check for conformance by comparing a priori process models to the event log of the same process, and to enhance existing process models based on information in the corresponding event log of the actual process (van der Aalst 2016).

Since its emergence in the mid-90s (Agrawal et al. 1998), research on process mining has mainly focused on advancing the technological basis by developing more refined algorithms for process discovery and conformance checking (for a detailed review, see Augusto et al (2019)), new methods for event log pre-processing (Mannhardt et al. 2019), and suitable process mining tools (Turner et al. 2012). Recently, a growing body of literature has emerged that recognizes the application of process mining in an organizational context. However, in this regard, the extant literature mainly focuses on the technical perspective of implementing process mining in organizations rather than on the sociotechnical implications of using it in an organizational context. For example, several studies investigate the application of different process mining algorithms in specific domains, such as healthcare (Farid et al. 2019), education (Ghazal et al. 2017), and supply chains (Jokonowo et al. 2018). In addition, extant literature addresses the application of process mining across industries to compare prevailing source systems and techniques (Dakic et al. 2018; Thiede et al. 2018).

Only recently, the first studies emerged to shed light on the sociotechnical implications of process mining, such as the necessary organizational antecedents, for example, a structured project management approach (Mans et al. 2013) and collaborative practices to evaluate the data and analyses (Eggers and Hein 2020), as well as potential managerial challenges (Grisold et al. 2020) when implementing the technology. Yet, these studies are but the beginning as the implications of the pervasive transparency created from process mining still remain unclear (Grisold et al. 2020), in particular in the light of emerging challenges, such as the fear of control and privacy loss (Grisold et al. 2020; Mendling et al. 2020).

2.2 Process Awareness

The concept of process awareness is rooted in research on organizational process orientation (Davenport and Short 1990; Hammer and Stanton 1999) and refers to the notion of employees being aware of how they perform their—often subconscious—routines, how their work is embedded in the overall process, and how their actions are linked to internal and external stakeholders (Leyer et al. 2018). Therefore, process awareness is considered a critical antecedent for organizations to shift their focus from managing and optimizing functional silos to achieving comprehensive process optimization across functional and departmental boundaries (Dumas et al. 2018).

Essentially, business processes can occur, and thus, be managed at three different organizational levels. Stemming from Taylorism, organizations traditionally focused on optimizing inter-individual processes, that is, sub-processes that are executed within small workgroups and departments (Davenport and Short 1990). However, in their seminal article on process orientation, Davenport and Short (1990) urged organizations to orient process management towards inter-functional processes, that is, processes that are carried out within the organization, but across functional or departmental units, and inter-organizational processes, that is, processes that are occurring between two or more organizations. Thereby, organizations achieve an orientation towards end-to-end processes, that is, "*processes that interface with customers and suppliers of the organization*" (Dumas et al. 2018, p. 49). Only through process orientation can firms optimize their increasingly interrelated, collaborative, and flexible processual reality (Davenport and Short 1990; Dumas et al. 2018). While process orientation requires various substantial organizational changes, such as a process-oriented structure, roles (Christiansson and Rentzhog 2019; Danilova 2019), and culture (van Assen 2018), there is consensus that the first step towards process orientation is the inward look (Kohlbacher and Gruenwald 2011). Only if the firm and its members are fully aware of the current process landscape with all variations and interrelations will they be able to define and implement organizational changes (Kohlbacher 2010).

Yet, achieving process awareness is a challenging endeavor. First, creating the necessary transparency on business processes is difficult as processes and actions are often not named, the quantity of processes and variations is unknown, the processes are not documented in maps or charts, process boundaries are not clearly defined, and process knowledge is highly fragmented across the organization (Corallo et al. 2010; Kohlbacher and Gruenwald 2011). Second, to effectively identify and communicate business processes, employees require a shared process understanding (Christiansson and Rentzhog 2019). However, creating a shared process understanding is difficult as employees rely on their individual perceptions of processes and might lack a shared language to refer to processes and activities (Dumas et al. 2018; McCormack and Rauseo 2005).

To this end, research on the overarching field of BPM has yielded several methods for creating process awareness. Traditionally, BPM provides interview-based and workshop-based process discovery methods (Dumas et al. 2018) that rely on process experts eliciting and capturing process knowledge from domain experts. Even though these approaches provide rich insights and the setting to develop a shared process understanding, they are time-consuming and rely on the often limited ability of domain experts to recall the entirety of their working routines (Rosemann 2006; Seethamraju and Marjanovic 2009). Therefore, these approaches are complemented by evidence-based process discovery methods, such as analyzing existent process documentation or observing process operators (Dumas et al. 2018). All methods, however, are based on subjective perceptions of a process. The resulting process models can be distorted to be incomplete, outdated or reflect the process view of individual experts (Malinova and Mendling 2018) who are usually very knowledgeable regarding their own tasks but lack an understanding of the overall process context they are embedded in (Dumas et al. 2018; McCormack and Rauseo 2005). Therefore, creating and communicating transparency on inter-functional and inter-organizational processes is still considered a challenge (Corallo et al. 2010; Leyer et al. 2018). With the advent of automated, evidence-based process discovery techniques, such as process mining, the opportunity emerges to create organizational process awareness that is no longer dependent on individual perceptions (Mendling et al. 2020). However, we still lack an understanding of how organizations engage with the transparency created from process mining (Grisold et al. 2020) and how the technology facilitates the emergence of process awareness (Eggers and Hein 2020).

3 Methodology

3.1 Research Design

Studying the mechanisms that lead organizations to create increased process awareness from process mining involves a complex and context-sensitive research setting. We, therefore, considered a qualitative case study approach to be particularly suitable for investigating such a novel and complex phenomenon (Dubé and Paré 2003; Yin 2014). In particular, we chose an exploratory, multiple case study research approach aimed at building theory (Eisenhardt 1989) since we still lack an understanding of how organizations engage with transparency through process mining to achieve process awareness (Grisold et al. 2020). To develop a theory of how organizations create process awareness from process mining, we entered the field with no prior theory and hypotheses to avoid bias and limiting the findings (Eisenhardt 1989). We selected four cases to study the respective organization's process of using and creating process awareness from process mining as the unit of analysis (Dubé and Paré 2003). By studying multiple cases, we could explicitly consider the specific usage contexts of process mining, enabling us to deepen our understanding and explanations for the observations made (Miles and Huberman 1994). Thus, we adopted a theoretical replication logic as we predicted contrasting results from the cases for anticipatable reasons due to the case context (Eisenhardt and Graebner 2007). Therefore, the choice of the four cases was based on a theoretical sampling approach using the principles of similarity and contrast (Miles and Huberman 1994) so that the chosen cases were considered useful in providing rich insights into the research question (Eisenhardt 1989).

We ensured similarity across the cases regarding the critical aspect of our research question, i.e., process mining in an organizational context. Therefore, we selected organizations that had used process mining for at least four years to ensure they had implemented several process mining projects, from requirements analysis to implementation to evaluating and using the results. In this way, we could account for the fact that technical issues that may initially complicate the implementation of process mining (van der Aalst et al. 2011) do not obscure the mechanisms that lead to process awareness. However, we presumed these mechanisms vary depending on (1) the specific process and industry context for which process mining is applied by the organization and (2) the company size and structure. We argue that (1) the specific process and industry contexts, such as an internal production process or a cross-organizational purchasing or customer process, are important since they might impact how the stakeholders involved in a process generate a shared process awareness from process mining. For example, internal process stakeholders might already share a specific common process language that external process stakeholders lack, thus requiring different mechanisms to create process awareness. We also aimed to consider industry-specific characteristics, such as machine-intensive, rigid processes in production, or flexible, customer-centric processes in the service industry. Second, we consider (2) the company size and structure to be influential on mechanisms for creating process awareness from process mining. For example, the members of a medium-sized, local organization might be more familiar and closely connected to use process mining jointly. In contrast, a large, multinational organization might need to establish mechanisms dedicated to enforcing the collaboration on process mining across departments and locations. Table 1 gives an overview of the four selected cases.

3.2 Data Collection

To ensure construct validity, we used multiple sources of evidence and engaged in data triangulation (Yin 2014). We conducted 24 semi-structured, in-depth expert interviews

Table 1 Overview of the case studies

Pseudonymized name	Industry	Years of process mining experience	Company size (based on 2019 revenue)	Number of employees (as of 2020)	Process mining focus
ManuCorp	Electrical equipment; Multinational corporation	8	> €28 billion	> 100,000	Internal processes (internal supply chains)
DistriCorp	Wholesale; German company	6	> €0.1 billion	< 200	Cross-organizational processes (procurement and warehousing)
PensionCorp	Financial services; Dutch company	4	> €0.8 billion	< 3,000	Cross-organizational processes (customer journey)
AutoCorp	Automotive; Multinational corporation	4	> €100 billion	> 120,000	Internal processes (development and production)

€ = Euros

(Myers and Newman 2007) across the four organizations, with a total duration of over 19 h, and collected archival data, such as case studies, blog entries, videos, and newspaper articles. An overview of the interviews and the collected archival data is displayed in Table 2.

For the expert interviews, we developed a semi-structured interview guideline with open-ended questions included in Appendix A. As we aimed to unravel the mechanisms that lead to process awareness through process mining-induced transparency, we addressed the following areas of inquiry: why and how the organization implemented process mining, the mechanisms and factors that enabled the implementation and use, and the outcome, i.e. transparency and process changes, that they achieved from applying process mining to specific processes. We aimed to represent a "*variety of voices*'' (Myers and Newman 2007). Thus, we interviewed various roles related to process mining use across the organizations, including data scientists, IT experts, process owners, and executive managers. As each of the four cases has a different focus of process mining analyses, we ensured to include business experts from the departments involved in the process mining analyses, such as production or procurement. Beyond the interview data, some informants were willing to give a demonstration of how they use process mining so we could gain deeper insights on how they analyze their processes and what findings they obtain. Our sources for archival data included the companies' websites, websites of process mining vendors and process mining consulting companies, and peer-reviewed as well as (online) media articles pertaining to the firm's process mining use. Finally, to ensure reliable results, we maintained a chain of evidence and developed a case database (Yin 2014).

3.3 Data Analysis

To conduct the data analysis, we engaged in within-case and cross-case analysis (Eisenhardt 1989), following a grounded theory coding process (Glaser and Strauss 1967). This approach consists of the open coding of first-order concepts from the qualitative data that describe the phenomenon of interest, i.e., how transparency through process mining leads to organizational process awareness. We assigned the open codes at the level of the within-case analysis, that is, we coded and analyzed each case individually. Then, we formed the second-order constructs using axial coding to establish the interrelationships between the codes. To this end, we compared first-order codes across cases to recognize cross-case patterns and interrelations. In the last step, we conducted selective coding to aggregate dimensions that describe relating second-order constructs (Gioia et al. 2013).

Starting with open coding, we used a line-by-line coding approach to extract factors and mechanisms that might be relevant for creating process awareness through process mining for each case. We adhered closely to the informants' and archival sources' language and developed over 400 open codes. We discussed these open codes and aggregated codes that were clearly redundant, for example, "*discussing analyses with other departments*" and "*cross-departmental collaboration to evaluate process mining*". Our final set comprised 389 codes reflecting how, why, and to which result each of the firms used process mining. Next, we discussed the set of open codes to find similarities and differences among the codes and assemble them into more theoretical categories (Gioia et al. 2013). While constantly comparing the data and emerging codes, we aggregated the first-order codes into 11 second-order themes that are specific to the organization's chosen governance approach (i.e., a top-down or bottom-up approach).

Table 2 Overview of the interviews and archival data sources

Pseudonymized company name	Position of informant	Years of process mining experience	Duration of interview (hh:mm)	Number & type of archival sources collected for the case
ManuCorp	Head of Process Analytics	4 years	00:35 & 00:45	6 (case study, presentation, videos, blog entry, newspaper article)
	Regional Process Mining Manager	2 years	00:54	
	Regional CIO	8 years	00:58 & 01:02	
	IT Project Manager	3 years	00:32	
	Sales Manager	4 years	00:51	
DistriCorp	Chief Executive Officer	6 years	01:10	9 (presentations, videos, blog entries, case study, demonstration during interview)
	Chief Process Officer	6 years	01:02 & 00:39	
	Process Mining Developer	3 years	00:53	
	Process Owner Procurement	4 years	01:02	
	Procurement Controller	4 years	00:59	
	Process Manager Procurement	6 years	00:52	
PensionCorp	Data Scientist	2 years	00:42	7 (case studies, newspaper articles, blog entry)
	Head of Customer Analytics	4 years	00:54	
	Head of Analytics	4 years	00:34 & 00: 29	
	Project Manager Customer Processes	3 years	00:47	
AutoCorp	Project Manager Change Management	2.5 years	00:45	7 (presentations, video, case study, newspaper articles, demonstration during interview)
	Process Owner Development	1.5 years	00:48	
	Process Mining Developer Production	3 years	00:51	
	Process Mining Developer	3 years	00:52	
	Head of Process Mining	3 years	00:42	

The second-order themes reflect mechanisms and moderators that enabled the firms to achieve different forms of process awareness from process mining. In the final phase, we distilled the second-order themes into aggregate dimensions and assessed the relationships among the identified themes (Gioia et al. 2013). As a result, we obtained six aggregate dimensions that represent the different forms of process awareness achieved by using process mining, depending on the governance approach. The resulting data structure, representative quotes, and archival entries are displayed in Appendix B.

4 Results

The multiple case study yielded insights into how the four organizations implemented and used process mining to achieve process transparency and increased process awareness. In the following, we describe the process that emerged for each firm, from its initial situation before using process mining to the mechanisms for using the technology to generate process transparency and the outcomes achieved that contributed to the firm's path towards process awareness.

4.1 ManuCorp: Process Mining for Internal Supply Chains

4.1.1 Situation

Before ManuCorp first introduced process mining in 2013, the multinational organization faced a highly decentralized process landscape that was managed based on observational evidence and lacked clear responsibilities for end-to-end processes.

As the internal supply chain processes are the backbone of the firm's production business, realizing synergies in their supply chains has always been of major importance to ManuCorp. However, despite the close interdependence between the divisions through supplier and customer relationships, responsibility for process design and optimization remained with each division. As a consequence, the more than 50 ERP systems implemented throughout the corporation "*are all individually configured per division. So, each division decides what their processes look like and how they use the systems*" (Head of Process Analytics). The resulting internationally fragmented process landscape was managed locally by each division. However, ManuCorp lacked the database and mechanisms for creating awareness of end-to-end processes across divisions, for example, from customer order via production to delivery. Even though everybody had "*a bad feeling that things were not going well, we did not know what the problem was*", as a regional CIO explained. Instead, whenever a division faced process complications, such as late deliveries, the responsible division manager brought together the department leaders, and then "*everybody started to argue and was trying to show that it was not their department's fault*" (Head of Process Analytics). The divisions tried to substantiate the claims with key performance indicators (KPIs), such as the rate of on-time delivery (OTD). However, these had to be calculated manually using data from the ERP systems. In addition, the KPI definition varied from department to department.

4.1.2 Standardized Monitoring of Sub-Processes

To encounter the situation of the locally managed process landscape based on individually calculated process KPIs, in 2013, ManuCorp's executive management introduced process mining to monitor the firm's processes and standardize process reporting. The international roll-out was directed in a top-down approach by the management, who decided on standardized analyses to be used in each division. In particular, every division was now required to use process mining to monitor their sub-processes, such as local warehousing and sales processes, in terms of OTD. To this end, a process mining center of excellence (CoE) was established to support the divisions in implementing the analyses and to provide data literacy training for employees. Yet, although the roll-out was intended to enable more than 3,000 process mining users across the organization, the workforce showed resistance to adopting the new technology, as a regional process mining manager noted: "*Using process mining to measure the OTD became mandatory, and many people felt taken by surprise and overwhelmed by the data complexity.*" In addition, regional managers perceived process mining "*as a threat*" that would reveal their division's processes and thereby also expose all weaknesses. To expedite the still hesitant adoption, ManuCorp's management incentivized regional managers financially to adopt and promote process mining usage within their divisions. Thus, the division's OTD performance became part of the regional manager's compensation, and process mining was recommended to analyze and improve the KPI. While these measures established process mining for the standardized monitoring of local sub-processes, ManuCorp's management also expected the divisions to increasingly use process mining autonomously as an exploratory tool for detecting unknown process weaknesses. However, the exploratory use did not ensue as "*the majority [of employees] just takes a look at the OTD because they feel it is yet another monitoring tool they have to use. So, they do not explore and reflect on the reasons underlying this KPI*" (Regional Process Mining Manager).

4.1.3 Standardized Monitoring of End-to-End Processes

While process mining allowed for standardized monitoring of the divisions' sub-processes, ManuCorp's management noticed the persistent lack of monitoring across end-to-end processes. They suspected the underlying reason was the lack of responsibility for end-to-end processes. Therefore, new process owner positions were created that were in charge of "*end-to-end processes across divisional boundaries and who have the power to summon all process stakeholders to analyze the process with process mining and decide on changes*" (Sales Manager). The process owners implemented standardized analyses together with the representatives from the divisions to create and communicate end-to-end process transparency. Cooperation with other divisions, for example, enabled one process owner to leverage the aggregated data from factory sites, distribution centers, and the sales team to analyze the lead-to-sales process in a cross-divisional analysis.

4.1.4 Aggregating Knowledge of the Process Landscape

While the standardized monitoring of sub- and end-to-end processes led to increased transparency of ManuCorp's process landscape, the newly gained knowledge remained fragmented across divisions and process owners. Therefore, a governance board was established to provide the divisions, represented by their division managers, and process owners with a space to exchange information and insights from process mining:

> *We discuss how processes could be changed based on the process mining analyses, and we define the scope for new analyses, for example, how do we measure global processes? How can we analyze processes across divisions?* (Head of Process Analytics)

Thus, the board served as an exchange platform that enabled divisions to reflect their findings within the organization-wide context and thus, to integrate regional process knowledge on a global level. The resulting aggregated, standardized process knowledge was then shared by the managers with their divisions. To further enable the aggregation of process knowledge from a technical perspective and to provide a combined database for process mining, a centralized data lake was established incorporating data from enterprise systems across the organization, such as ERP and CRM systems.

4.1.5 Democratizing Knowledge of the Process Landscape

The previous measures facilitated the aggregation of standardized process knowledge across the global process landscape. Still, to operational employees, global process knowledge was available only through their managers or process owners who participated in the governance board. To democratize access to aggregated process knowledge and encourage employees' engagement in the firm's business process management, ManuCorp recently introduced a central process mining platform. The platform was designed to "*[store] all processes and interrelations of processes with their corresponding process mining analyses. Today, every employee can access the platform and point out process improvements*" (Sales Manager).

4.1.6 Outcomes

The top-down driven use of standardized process mining analyses enabled ManuCorp to increase process awareness regarding sub-processes, end-to-end processes, and the global process landscape. Based on the awareness, process changes at all levels were defined and implemented.

On the sub-process level, individual divisions used the standardized OTD analyses to achieve awareness of sub-processes and measure their performance with standardized KPIs. For example, one division's sales department became aware of their high rates of unnecessary price changes, which caused subsequent production delays, and therefore, decided on a new price management strategy.

On the end-to-end process level, ManuCorp's newly appointed process owners used process mining to create end-to-end process awareness and, thus, realized end-to-end process synergies. Taking the example of the cross-divisional lead-to-sales process analysis, the responsible process owner found that the reason for late customer deliveries was unnecessary price coordination between some divisions involved in the process. Thus, the process owner defined a standardized approach to price coordination across the divisions.

Process awareness of the global process landscape emerged from two sources. First, the governance board enabled division managers to share their regional process knowledge and gain awareness of process interrelations on the global level. For example, through the governance board, a regional CIO detected process synergies between logistics centers, so that he decided to merge several warehouses into one strategically located shipping point. Second, as a result of the central process mining platform, access to process knowledge was democratized across divisions and hierarchies, giving all ManuCorp employees equal opportunities to know, reflect and potentially improve the firm's process landscape.

4.2 DistriCorp: Process Mining for Procurement and Warehousing

4.2.1 Situation

DistriCorp, as a wholesaler, is dependent on its efficient procurement and warehousing processes. However, before the medium-sized organization first introduced process mining in 2014, it was challenged by stagnating improvement of throughput times in the warehouse. This situation was complicated by a lack of awareness and responsibilities for optimizing end-to-end processes.

Even though DistriCorp had focused on optimizing its warehousing processes, for example, by automating the picking of goods, the organization faced the situation where "*warehouse throughput times had been optimized to the limit, but we did not know why we were still losing time before shipping orders*" (Chief Process Officer). The warehouse managers at DistriCorp suspected that the reason was the purchasing department that delayed the order of goods. In contrast, the purchasing department believed the sales department was the originator by forwarding incorrect data in the purchase order. As the CEO describes it, they "*experienced finger-pointing due to the lack of process awareness between departments*" since they missed the database and mechanisms to substantiate their suspicions with facts. The situation was further complicated as the organizational structure lacked end-to-end process owners who accounted for processes across departmental boundaries.

4.2.2 Standardized Monitoring of Sub-Processes

In 2014, DistriCorp introduced process mining as a technology to increase efficiency in the firm's procurement and warehousing processes. The implementation was led by the management in a top-down approach. To this end, a process mining expert team was established, consisting of an analytics expert, the newly appointed Chief Process Officer (CPO), and the firm's Chief Executive Officer (CEO). The expert team decided on KPIs, such as automation rates and OTD, and standardized process mining analyses to be implemented on the firm's core business processes, such as procurement and warehousing. However, even though the workforce received data literacy training to comprehend process mining, they were hesitant to adopt:

> *"I had the feeling that I had to put my cards on the table and everybody would see if something is going wrong. Many people were afraid that they would get into trouble if something negative surfaced."* (Process Owner Procurement)

To resolve concerns about supervision, all personal information was anonymized in the database, and the executive management followed a clear communication strategy to assure that analysis results would not be used to disadvantage the departments. In addition, DistriCorp's executive management strived to increase the adoption of process mining within departments by adapting process mining to the needs of operational employees. Together with the process mining provider, DistriCorp developed a new "*control function*" of the process mining software that alerted operational employees of any unusual incidents within their sub-process, such as a delivery that is late to arrive. As the CPO pointed out, the "*employees immediately experienced the added value for their individual process, and they use it every day now*". However, the new feature led to employees only attending to the notifications but not using the tool's capability to explore processes, also beyond their department boundaries, due to "*perceiving it as overwhelming*". The CPO suspected that the reason for this was that employees, except for the expert team, had not been involved in the design and implementation process. Thus, while the individual departments intensified the use of the "*control function*" to monitor pre-defined irregularities within their sub-processes, the exploratory use of process mining to detect root causes remained absent.

4.2.3 Aggregating Knowledge within and across End-to-End Processes

However, it soon became clear that the root causes for process problems could only be identified by analyzing end-to-end processes:

> "*[…] we need to develop process mining analyses that strongly question departmental boundaries. Why should the customer care if our sales department does a great job of processing the order, but it's stuck in the warehouse?*" (CEO)

Therefore, the management created the new role of a CPO in charge of supervising all end-to-end processes. Thereby, the CPO became the central authority to aggregate process knowledge within and across end-to-end processes. To this end, the CPO was responsible for connecting with the representatives from the departments, who were monitoring sub-processes with process mining. The CPO engaged the departments to synthesize local process knowledge, identify end-to-end process improvement opportunities, decide on process changes, develop a common global process understanding, and communicate these findings top-down to the departments. Thereby, DistriCorp also became aware of cross-organizational process interrelations. For example, they leveraged internally available ERP procurement data to understand the impact of supplier behavior on procurement performance.

4.2.4 Outcomes

The top-down driven use of standardized process mining analyses at DistriCorp resulted in increased process awareness on the level of sub-processes, end-to-end processes, and the global process landscape. Based on the awareness, the CPO, together with representatives from the departments, decided top-down on process changes.

First, awareness of the sub-process level emerged as the new "*control function*" augmenting DistriCorp's process mining software notified operational employees of irregularities within their sub-processes. For example, purchasing employees were now alerted that "*the delivery date is due, but we have not received any order confirmation from the supplier, so we have to send a reminder*" (Procurement Controller). Thereby, the individual departments at DistriCorp became more efficient in resolving disruptions within the scope of their sub-processes.

Second, as the CPO encouraged exchanging process mining insights across departments, DistriCorp experienced an increased awareness of and cooperation in end-to-end processes. One example of end-to-end process awareness is the collaborative process mining analyses between the warehouse and the sales department at DistriCorp. The warehouse department found out they regularly shipped customer orders too late because of the sales department's online shop that allowed customers to enter unverified information. As a result, the sales department modified the online shop to include pre-defined fields to process and ship orders more efficiently.

Third, on a global process level, DistriCorp increased their awareness of the process landscape, also beyond their own organizational borders. For example, by drawing on information provided by their suppliers, such as shipment dates and expected delivery dates, the procurement analyzed the reliability of their suppliers and found out that some suppliers "*deliver the goods a few days early, with the best of intentions. However, this has an impact on our warehouse process as we had not expected the delivery, and there is no space in the warehouse*" (Process Owner Procurement). DistriCorp shared these insights with the suppliers who adapted their behavior to allow optimal cooperation.

4.3 PensionCorp: Process Mining for the Customer Journey

4.3.1 Situation

Due to market and regulatory changes, PensionCorp feared stronger competition in the financial services market and, therefore, in 2013, established a strategic program to optimize client-facing processes. However, before PensionCorp implemented process mining in 2016, the program was based on KPIs that were reported individually by departments across the organization and were difficult to interpret as they lacked contextual information.

Even though PensionCorp employed business intelligence (BI) tools to compute KPIs throughout the organization, the results were based "*on silos, and we did not have the analytical power to look into the underlying relations*" (Data Scientist). In addition, the reported KPIs lacked contextual information, which made it difficult to interpret the data correctly. For example, the term "partner" was referred to differently by individual departments – some defining it as a married couple, while others also subsumed registered partnerships under the term. Interestingly, PensionCorp had already established a data lake combining data from various sources across the firm to standardize and contextualize data. Yet, deriving insights from the data remained difficult since *"[we] had one location where all the data was combined. But we did not have the tools to navigate the data and find relationships across all the processes in the systems. Process mining was the answer to that"* (Data Scientist).

4.3.2 Exploring Sub-Processes

In 2016, PensionCorp's data scientists initiated a local project to investigate how process mining could help to analyze the wealth of event data stored in the central data lake. The data was characterized by high complexity as they originated from many process stakeholders within and outside of the firm. The pension registration process, for example, involves a customer's employer registering him or her for a pension, a firm subcontracted by PensionCorp administering the registration, and PensionCorp receiving the new customer. These sub-processes were supported by four different systems that, however, fed into the central data lake. After an initial analysis of the pension registration sub-process, the team found compliance problems and inefficient communication patterns. PensionCorp's executive management "*were surprised by the results, and then it was no question about them continuing with this technology*" (Head of Analytics). Thus, they decided to provide process mining services throughout the firm. A CoE was established to support the departments in implementing process mining analyses specific to their needs. Rather than prescribing standardized analyses in a top-down approach, PensionCorp's management chose a bottom-up approach in which departments could request process mining analyses to support their individual goals. To promote the technology within the firm, the CoE team provided data literacy training and inspiration for application scenarios:

> "*[…] we held community sessions, we talked to people, we demonstrated the technology and what we can do with it. […] In the beginning, we had to promote it, but now the departments know us, and they come to us. Now, we have even more work than we can take care of.*" (Data Scientist)

4.3.3 Exploring End-to-End Processes

However, while the departments explored sub-processes within their departmental boundaries, it soon became evident that the processual interrelations between departments required the end-to-end analysis and optimization of processes. For example, the ICT department explored why customers were not adopting the self-service channels they provided, such as online forms and websites. While the ICT department investigated how customers were using the self-service channels, they could not identify why some customers refrained from using the services. Therefore, they enriched their process mining analyses with customer survey data on satisfaction with the self-service channels from the communications department. As a result, they found out that for some customer groups, the online self-service was not providing the necessary features to manage all their affairs, and thus, the ICT department adapted the self-service portal. This example illustrates how the departments engaged in the exploratory usage of process mining, which allowed them to identify additional required data sources iteratively. These data sources, often belonging to other departments, provided them with additional pieces to the overall process picture:

> "*We used to think we had a lot of data within the data lake, but now looking at it with process mining, we see what data we lack, and we add that data.*" (Head of Customer Analytics)

But while the departments jointly explored end-to-end processes by drawing on data available internally and externally to their departments, PensionCorp's data scientists reported that the organization still lacked process awareness on a global level. Instead, "*every department within this company has its own process mining goals and KPIs, and that is hard to manage [for the CoE]. So, we leave the responsibility to conceptualize and work with the analyses to the representatives of the departments*" (Head of Customer Analytics). Thereby, the departments autonomously increase their awareness of end-to-end processes that they are embedded in but lack transparency on the overall process landscape.

4.3.4 Outcomes

Taking the analysis of the customer journey as a prominent example of the bottom-up driven process mining use at PensionCorp, we observed two prevalent outcomes concerning their awareness of the customer journey on the sub- and end-to-end process level and improved response to customer needs.

On the sub-process level, PensionCorp achieved increased awareness of inefficient segments of the customer journey. For example, the pension department discovered through the analysis of the pension claim process that they regularly required more time than promised to the customer to process pension claims due to unnecessary rework. Eliminating these unnecessary activities allowed the department to increase efficiency.

In addition, by drawing on internally and externally available data, the departments created awareness of the end-to-end processes they are part of and, hence, identified thus far unknown customer needs. For example, by using customer interaction data internally available at the customer service department, the team was able to create transparency on their customer interaction throughout the customer journey. Thereby, the process analysis revealed that a high volume of customer calls occurred once a year after information documents had been sent out to customers. Complementing these insights with customer survey data showed that "*the customers are calling a lot because the documents are not clear enough*". The insight was forwarded to the communications department, which then adapted the documents to the customers' needs.

4.4 AutoCorp: Process Mining for Development and Production

4.4.1 Situation

Having evolved over a century, AutoCorp is characterized by its complex system landscape with over 8,000 different IT systems and its intertwined production processes. Before introducing process mining in 2016, the organization faced increasing competition through new market entrants and thus, strived to increase process efficiency and agility. However, this was complicated by decentralized process management and the lack of awareness of process interdependencies.

Functional areas at AutoCorp, such as production or procurement, have been traditionally autonomous in designing and managing their processes. As a result, however, sub-processes were optimized within departmental silos without considering consequences for other departments, as this example illustrates:

> "*We would change the painting process, and then, all of a sudden, rework in assembly would skyrocket. However, before we used process mining, no one would notice that connection. There is no communication between these departments. They are located at the same plant, but they are led by different department managers, they have different tasks, and have nothing to do with each other.*" (Process Mining Developer Production)

The lack of awareness of process interdependencies had particularly strong implications for AutoCorp's change management. Any changes in the product development process require close alignment and adaption in the production process, as changes are costly and complex. Due to the silo-oriented process management, however, AutoCorp's change management struggled to "*process hundreds to thousands of change requests every day. […] We need to understand if these changes align with previous changes and how they affect downstream activities*" (Project Manager Change Management).

4.4.2 Exploring Sub-Processes

To encounter the lack of knowledge on process interrelations and their consequences, several bottom-up initiatives driven by AutoCorp's departments emerged to investigate process mining as new technology to illuminate unknown path dependencies. Upon the first successful initiatives, AutoCorp's executive management then established a process mining CoE to support the departments with collecting process data and implementing process mining analyses addressing their needs. Following a bottom-up implementation approach, the departments were free to define KPIs and analyses as required. For example, the production department analyzed sensor data from assembly to find the root causes for high rework rates in the paint shop.

4.4.3 Exploring End-to-End Processes

Supported by the CoE, the departments at AutoCorp engaged in the exploratory usage of process mining, which led to the incremental expansion of the analyses into the end-to-end process context. This development is illustrated by the change management department who initially extracted process data from their central change management system to analyze with process mining. However, "*rather than analyzing a process, we tried to analyze a system. We soon realized that the focus was too narrow and that we needed to consider the end-to-end change management process*" (Head of Process Mining). The team involved both the development and production side to analyze the end-to-end process. They iteratively identified additional data sources to be included, such as a system for managing error reports from production and another system for managing change requests from customers owned by the development department. However, the integration of additional data was challenging because access to the locally managed data sources was not always approved and required negotiations. Yet, they collaboratively implemented the process mining analyses to achieve transparency on the alignment between their sub-processes, as the process manager from development illustrated:

> "*We became aware of the predecessor and successor relationships of our departments. For example, we could see how many change requests our [development] project teams submitted to the change management team and how often they ended up not being implemented in production. Then we could discuss reasons for why the information flow failed.*"

In this way, departments at AutoCorp discovered how they had been neglecting the critical process transitions to other departments and had "*focused on being efficient within a silo, but never asked what happens in the next process step*" (Project Manager Change Management). However, even though the departments gained transparency on their processual interrelations, their insights remained inaccessible in the broader organizational context, preventing employees from developing process awareness on the global process level. As the Head of Process Mining reported, without a central authority to collect the emerging process knowledge, "*the findings persist within the respective departments, but they do not know about each other.*"

4.4.4 Outcomes

Taking the change management process analysis as an example for the bottom-up driven process mining usage at AutoCorp, we observe two outcomes. AutoCorp achieved an increased awareness of sub- and end-to-end processes and, based on the awareness, optimized the intra- and cross-departmental alignment of processes.

On the sub-process level, the departments at AutoCorp leveraged individually conceptualized process mining analyses that created intra-departmental sub-process transparency. For example, the change management department revealed through process mining that they carried out 3,000 different workflows to process change requests. Based on that insight, the department realigned the process by coordinating individual activities more effectively.

On the level of end-to-end processes, the awareness of cross-departmental process interdependencies at AutoCorp increased, driven by the departments' self-organized networking to create cross-departmental process mining analyses. Due to the traditionally self-reliant mode of operation at AutoCorp, process transitions between departments were a blind spot outside the responsibility of any department. However, resulting from the newly gained process awareness through process mining, the departments achieved improved transparency on and alignment of processes across departments. For example, by analyzing the change management process across departmental transitions, the team identified inefficient communication patterns between the development and change management departments that delayed the end-to-end process, which was improved through altered communication rules.

4.5 Cross-Case Comparison

Comparing the four cases, it became clear that the organizations developed different mechanisms to implement process mining, increase its intra- and cross-functional use, and achieve process awareness. Depending on the mechanisms, the firms created a shared intra- or cross-functional or cross-organizational process awareness through process mining. By leveraging this process awareness, the organizations derived process changes that advanced their individual company goals. We provide a detailed comparison of the cases in Table 3. Interestingly, we observe that these mechanisms depend not on the process and industry

Table 3 Cross-case comparison regarding the governance approach, goals, mechanisms, and outcomes of process mining usage

Case	Governance approach	Initial situation and purpose of process mining use	Mechanisms				Outcomes	
			Change in organizational structures	Process mining use on the sub-process level	Process mining use on the end-to-end process level	Process mining use on the global process level	Process awareness	Process change
ManuCorp	Top-down driven process mining implementation	Fragmented, locally managed process landscape Inconsistent process KPI reporting Purpose: standardized analysis and reporting of the firm's processes	Establishment of a process mining CoE Establishment of a Governance Board and process owners Implementation of a data lake Providing data literacy training	Standardized monitoring of OTD within divisions Increasing within-division use of process mining by incentivizing middle managers	Aggregating end-to-end process knowledge through process owners as central authorities Communicating process knowledge top-down to the divisions	Aggregating global process mining knowledge through the Governance Board as central authority Communicating process knowledge top-down to the divisions Democratizing access to process knowledge through a process mining platform	Standardized awareness of intra-departmental sub-processes Standardized awareness of cross-departmental end-to-end processes Standardized awareness of global process variations and dependencies Shared global process awareness resulting from the democratization of process knowledge	Increased sub-process efficiency Realization of end-to-end process synergies Realization of cross-divisional process synergies
DistriCorp		Stagnating process efficiency Lack of awareness of and responsibilities for end-to-end processes Purpose: increase the efficiency of procurement and warehousing	Establishment of a process mining expert team Establishment of a CPO Providing data literacy training	Standardized monitoring of process performance within departments, such as procurement and warehousing Increasing within-department use of process mining through adaption of tool to provide "control function"	Aggregating end-to-end process knowledge through CPO as central authority Communicating process knowledge top-down to the departments	Aggregating global process mining knowledge through the CPO as central authority Communicating process knowledge top-down to the departments	Standardized awareness of intra-departmental sub-processes Standardized awareness of cross-departmental end-to-end processes Standardized awareness of cross-organizational processes	Increased sub-process efficiency Increased end-to-end process efficiency Optimized cross-organizational cooperation
PensionCorp	Bottom-up driven local process mining initiatives	Dissatisfaction in customer-facing processes Lack of end-to-end process reporting Purpose: improve customer satisfaction through improved customer-facing processes	Establishment of a process mining CoE Providing data literacy training	Exploratory use of process mining within departments, i.e., for customer service	Self-organized collaborating across departments to create cross-departmental process mining analyses Enriching the data lake iteratively with additional data, e.g., with customer survey data	*No use of process mining on the global process level was observed*	Shared awareness of intra-departmental sub-processes from the customer's perspective Shared awareness of the end-to-end customer journey	Increased awareness of customer needs within sub-processes and end-to-end processes Improved response to customer needs within sub-processes and end-to-end processes
AutoCorp		Complex and intransparent process interrelations Decentralized, silo-bound process management Purpose: create transparency on process interdependencies	Establishment of a process mining CoE Providing data literacy training	Exploratory use of process mining within departments, i.e., for change management	Self-organized collaborating across departments to create cross-departmental process mining analyses Integrating locally managed data sources iteratively, e.g., from production	*No use of process mining on the global process level was observed*	Shared awareness of intra-departmental sub-process dependencies Shared awareness of end-to-end process interrelations	Increased intra-departmental process alignment Increased cross-departmental process alignment

context. For example, we see that ManuCorp, a multinational manufacturer, and DistriCorp, a medium-sized wholesaler, both developed similar top-down driven communication mechanisms to foster process mining use and transparency within and across departments. In contrast, PensionCorp, a local financial service provider, and AutoCorp, a multinational manufacturer, employed similar bottom-up driven exploration mechanisms that iteratively led to process awareness within and across departments. Consequently, the chosen governance approach for conducting process mining plays a decisive role in creating mechanisms that foster process awareness. We will discuss the implications of this observation in the following.

5 Discussion

Combining the results of the multiple case study, we observe that firms employ seven mechanisms to achieve increased process awareness through process mining. The resulting process awareness either pertains to the inter-individual process level, that is, stakeholders from one department share awareness of their sub-process, or the inter-functional level, that is, stakeholders across departments share awareness of the end-to-end process. In addition, process awareness on an intra- and inter-organizational level can be achieved, that is, organizational stakeholders share awareness of the firm's overall process landscape, including processes across different functions and organizations. The mechanisms leading to process awareness primarily emerge from the firm's process mining governance approach, i.e., bottom-up or top-down, and they are influenced by the firm's capability to facilitate a shared process language, a standardized data infrastructure, and aggregated process knowledge. In the following, we discuss the mechanisms according to the governance approach and then embed them in previous research on process mining and business process management.

5.1 Bottom-up Exploration Mechanisms Leading to Increased Process Awareness

The first group of mechanisms to become apparent from the multiple case study relates to the exploratory use of process mining in a bottom-up approach (see Fig. 1). Firms such as AutoCorp and PensionCorp engage in a department-driven use of process mining, meaning that departments are free to define and implement analyses autonomously without requirements imposed on them by the firm's management. As a result, the departments explore their analyses and achieve increased process awareness on the inter-individual and inter-functional process levels.

The first mechanism enables the narrowest form of process awareness on an inter-individual level and emerges from the exploratory use of process mining within one department based on internally available data sources. We have seen this in the example of AutoCorp's production department that explored the root causes for rework in the paint shop based on sensor data. Exploring the sub-process through process mining, the department's employees reflect their own behavior in relation to their peers' actions and thus develop a shared internal awareness of their departmental sub-processes. This awareness-building process is influenced by the fact that they share a common process language. Such a shared process language arises, for example, from the data literacy training offered by each of the companies' process mining CoE. By providing standardized training on understanding process data and conducting process mining analyses, employees develop a common vocabulary to discuss their processes. When evaluating their intra-departmental process mining analysis, a common vocabulary helps create a shared perspective on a jointly performed sub-process. The resulting shared internal process awareness enables the department to define the necessary process changes to overcome identified weaknesses. Consequently, the department internally shares a newly designed routine that is grounded on a shared process awareness facilitated by process mining. However, the shared awareness and the resulting process changes represent a local solution pertaining to the department's sub-process without acknowledging the overarching end-to-end process.

Yet, whenever the local process mining analysis indicates that the root cause for a process weakness is not located within the department's sub-process, the context of the end-to-end process becomes important. Thus, in the second mechanism, the department draws on internal data to explore process steps external to the department so that a shared process awareness on an inter-functional level is achieved. What might sound counterintuitive can be observed in the example of PensionCorp, where the customer service department used customer interaction data available in their systems to develop an understanding of how their clients perceived certain documents provided by the communications department. In this way, one department overcomes its bounded silo thinking by exploring internal process data that shed light on the overarching inter-functional process and, as a result, develops an awareness of the end-to-end process it is embedded in. Consequently, rather than seeking a local optimum, the department strives to infer changes that optimize the overarching end-to-end process.

Alternatively, as a third mechanism, the department draws on external data to explore further phases of the end-to-end process so that a shared process awareness on an

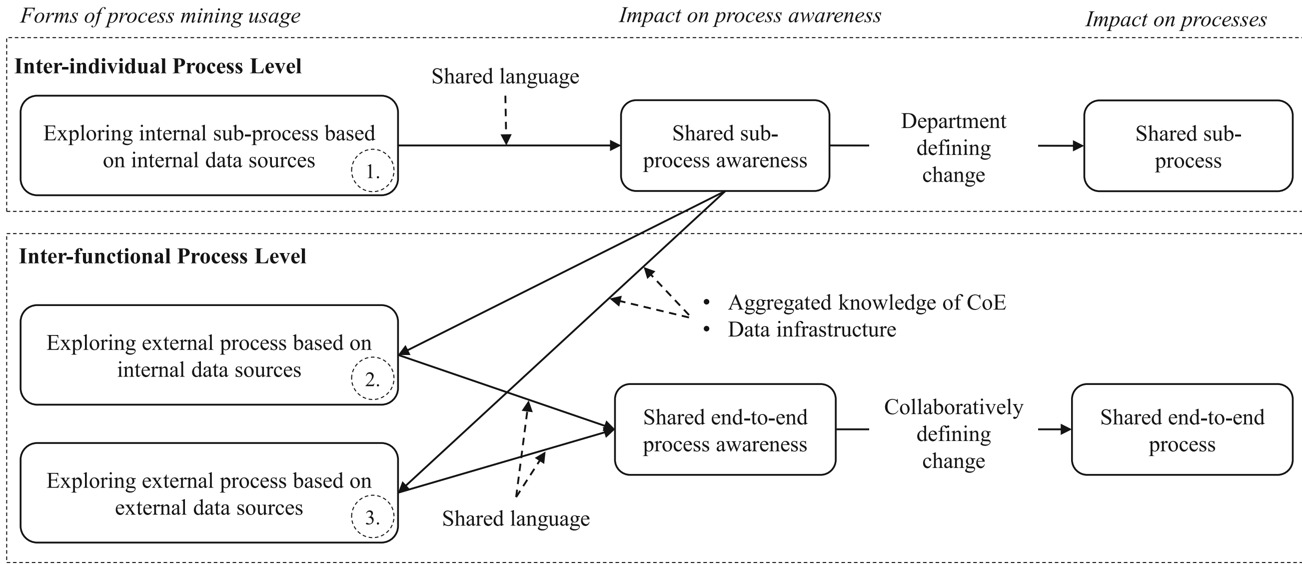

Fig. 1 Mechanisms of bottom-up exploration leading to increased process awareness

inter-functional level is achieved. The external data is provided by other stakeholders of the end-to-end process, such as other departments. Consider as an example AutoCorp, where the change management department initially analyzed their local sub-processes before they recognized the need to include data from other functions, such as development and production, to understand the end-to-end change management process. In the cases we observed, this search process is impacted by the process mining CoE that has aggregated a wealth of process knowledge through implementation projects in various departments and gives guidance on data sources that could be valuable to explore. Still, it can be challenging to gain access to the data needed, as seen in AutoCorp's example, since they might be under the decentralized governance of individual departments. In addition, data might be available in different formats across systems, presenting a technical challenge. Therefore, a centralized data infrastructure, such as the data lake established by PensionCorp, facilitates the search of and access to (potentially standardized) data. Finally, the joint analysis of process data with stakeholders from the related functions leads to a shared end-to-end process awareness. This joint effort is again facilitated by the shared process language that actors across the organization have acquired from standardized data literacy training. Resulting from the shared end-to-end awareness, process stakeholders collaboratively decide on process changes that reflect not only local optima but an optimum of the end-to-end process.

5.2 Top-Down Monitoring Mechanisms Leading to Increased Process Awareness

The second group of mechanisms resulting from the multiple case study relates to what we call the monitoring usage of process mining in a top-down approach. Firms, such as DistriCorp and ManuCorp, engage in a management-driven use of process mining, meaning that a central authority is deciding on application areas and standardized analyses. Departments are then required to engage with the standardized analyses to monitor pre-defined process characteristics. This process mining usage enables increased process awareness on the inter-individual level. However, firms pursuing a top-down approach engage in additional mechanisms to increase process awareness on the inter-functional level and the intra- and inter-organizational level (see Fig. 2).

The fourth mechanism enables shared process awareness on the inter-individual process level and resembles the inter-individual mechanism in a bottom-up approach. Contrary to a bottom-up approach, however, departments must use standardized process mining analyses in a top-down approach. Therefore, rather than engaging in autonomous exploration, the departments monitor assumedly relevant aspects of a process. The standardized investigation of known process problems can be of great value, as demonstrated by ManuCorp. By establishing a standardized OTD definition and providing appropriate training across the organization, departments used process mining to internally develop a standardized process awareness and infer necessary process changes to optimize their sub-processes. However, the other side of the coin is the lack of exploration that potentially reveals previously unknown

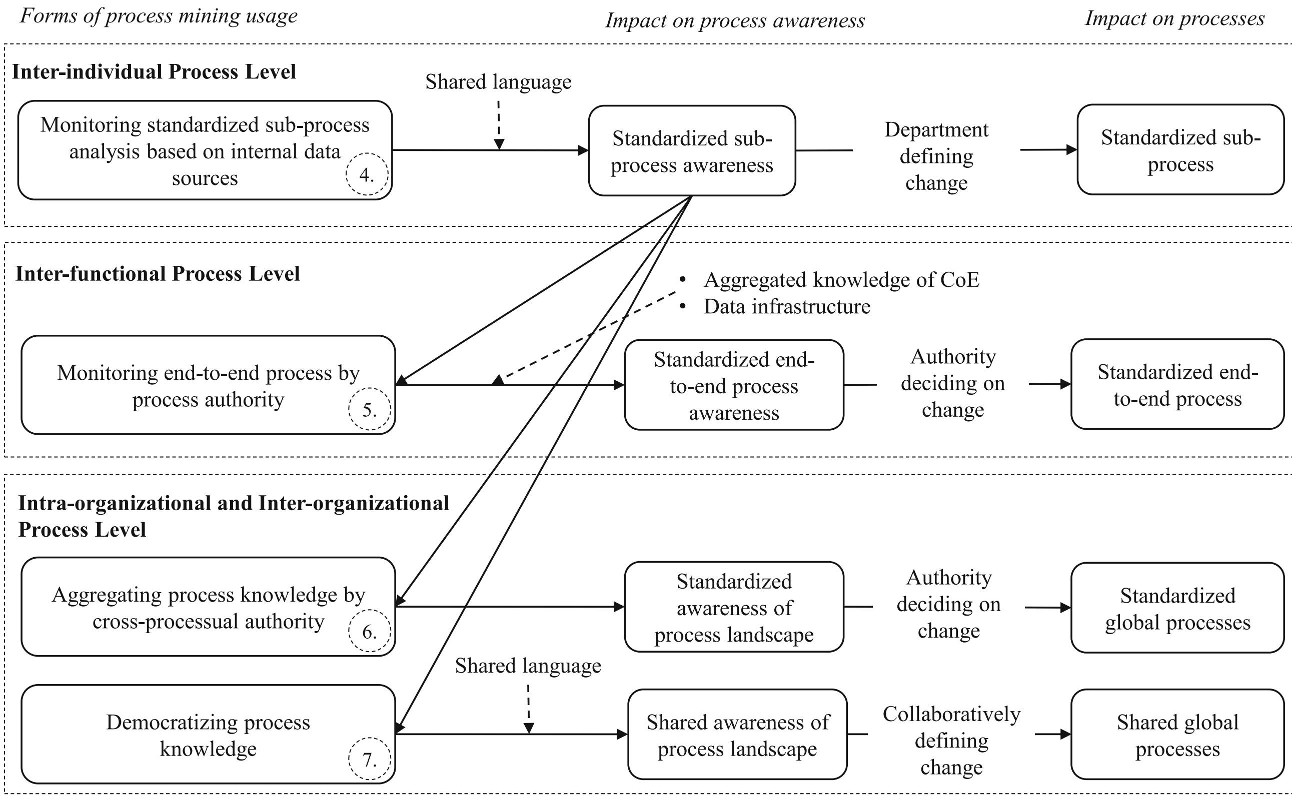

Fig. 2 Mechanisms of top-down monitoring leading to increased process awareness

problems, as observed in the example of ManuCorp where the departments remained limited to studying pre-defined criteria within their silos. Broadening this bounded usage to include the end-to-end process context requires managerial intervention.

In the fifth mechanism, process awareness on an inter-functional level is created through a process authority established by the management, such as process owners responsible for engaging stakeholders and acquiring data to facilitate end-to-end process mining analyses. An example is ManuCorp, where concurrent to the implementation of process mining, the management established the role of process owners responsible for involving end-to-end process stakeholders and defining standardized analyses to gain process transparency across divisional boundaries. Depending on the firm's data infrastructure, the implementation of the analyses is facilitated by centralized, standardized data sources. In addition, the CoE supports the identification and transformation of process data. After performing the analyses, the process owner communicates aggregated insights to the departments and finally decides on process changes. Thereby, the stakeholders involved in an end-to-end process, such as the lead-to-sales process at ManuCorp, are provided with a standardized process awareness by the process owner, contributing to a standardized process execution across departments. Yet, while process owners are responsible for the end-to-end process level, they are limited in their power and knowledge to optimize the overall process landscape.

Therefore, the sixth mechanism addresses the awareness of the firm's overall process landscape at the inter- and intra-organizational levels. This mechanism evolves as the management establishes a cross-processual authority, such as a CPO at DistriCorp or a Governance Board at ManuCorp, responsible for aggregating the departments' local process mining knowledge. For example, DistriCorp's CPO regularly meets with representatives from the departments to exchange the results of their process mining analyses. Note that, contrary to the role of a process owner, this authority acts on a cross-processual level, meaning that process mining insights are not only discussed within but across diverse end-to-end processes that connect different departments and organizations. Thereby, the cross-processual authority aggregates process mining knowledge that reflects the firm's overall process landscape. Through centrally aggregating individual departments' process mining findings and reflecting the synthesized knowledge into the silos, they develop a shared awareness of the process landscape that enables processual change towards standardization. However, as seen with ManuCorp, the resulting process knowledge is controlled by the process authority so that not everyone has equal access to it.

Therefore, the seventh mechanism creates awareness of the firm's overall process landscape at the inter- and intra-organizational levels and democratizes access to it. An example is the central process mining platform introduced by ManuCorp's management that enables employees to access all process mining analyses. Facilitated by preceding data literacy training provided by the CoE, employees can evaluate the analyses and build process awareness beyond their processual silos. As the process of building awareness is not controlled by a central authority, it emerges individually from the departments while employees interact with the process platform. Even though the process understanding might vary between departments, it is no longer informed only by individual perceptions but grounded on a unified fact base that reflects the global process landscape. We, therefore, expect a shared awareness of the firm's process landscape to emerge over time within and between departments which they draw on to inform and design shared global routines. We see this in the example of ManuCorp, where employees use the process platform to understand the global relationships between suppliers, customers, and production plants and express process optimization potentials.

5.3 Theoretical Implications

Overall, our research contributes towards understanding how organizations act upon the unprecedented transparency created through process mining (Grisold et al. 2020; Mendling et al. 2020) and how they leverage the transparency to benefit from increased process awareness (Eggers and Hein 2020). To this end, we identified seven mechanisms that enable organizations to achieve increased process awareness from process mining. Thereby, our study contributes to research on business process management and process mining in three ways.

First, our study contributes to research on business process management by revealing process mining as a new, data-driven way of creating process awareness. Creating process awareness throughout the organization is viewed as a major challenge, primarily due to a lack of a shared process language (Christiansson and Rentzhog 2019; Dumas et al. 2018) and difficulties in creating process transparency and a shared process understanding across organizational silos (McCormack and Rauseo 2005). While there are multiple techniques known from BPM research for creating process awareness, process mining is differentiated by its data-driven, automated discovery approach. The interview-based and workshop-based process discovery methods traditionally used in BPM (Dumas et al. 2018) serve to develop a common understanding and discover rationales behind certain actions, but at the same time they are at risk of resulting in subjectively influenced, incomplete process models (Rosemann 2006; Seethamraju and Marjanovic 2009). As evident from research on human memory and recollection, such procedures are prone to cognitive bias and—intentional or unintentional—omission (Okado and Stark 2003), which bears the risk of subjectively impacting or skewing the resulting process awareness. Even the evidence-based process discovery methods, such as the analysis of existent process documentation or the shadowing of process operators, depend on individual observations and potentially outdated or momentarily created material that usually reflects only a fraction of the firm's living process landscape (Dumas et al. 2018; Malinova and Mendling 2018). In that light, process mining can be understood as a technology-enabled evidence-based discovery method that relies on objective data to create process transparency on a firm's overall process landscape independent of subjective impressions—however, given that process activities are traced in corresponding IT systems (van der Aalst 2016). Drawing on this transparency, process stakeholders can engage in a dialogue to explain rationales or exchange experiences—similar to established BPM approaches—while relying on a current, objective fact base. Thereby, process mining can facilitate the emergence of a shared process language (Christiansson and Rentzhog 2019) in the firm by offering a standardized, objective reference frame when discussing processes. In addition, process mining supports the development of a shared process understanding (McCormack and Rauseo 2005) by providing an objective, up-to-date fact base that potentially reflects the firm's entire process landscape, which employees can jointly explore and discuss.

Second, our research reveals that while the use of process mining enables mechanisms for creating process awareness, the mechanisms and resulting type of awareness largely depend on the firm's chosen process mining governance approach, i.e., top-down or bottom-up driven governance. While previous research points towards the importance of adopting a structured process mining approach to achieve valuable and reliable process transparency (Aguirre et al. 2017; Mans et al. 2013), the overarching governance structures that enable firms to leverage such transparency for their benefit remained unknown (Mendling et al. 2020; vom Brocke et al. 2014). On the one hand, our study provides evidence that organizations are adopting a top-down process mining governance approach to further awareness and standardization of sub-processes as departments are required to adopt the technology for monitoring specified process KPIs. While that is valuable in the light of creating awareness for process performance within departments, the firms yet struggled with establishing the self-governed, exploratory use of process mining across functions to discover unknown process complications. One reason may be that employees had not been involved in the design and implementation of process mining analyses and thus were unaware of the technological capabilities—a complication that results in low perceived usefulness, which is known as a major factor influencing technology adoption in IS research (Venkatesh et al. 2003). In addition, this observation may be due to the sociological phenomenon known as the streetlight effect, which implies that humans tend to search where it is easiest and most obvious to look while neglecting the exploration of alternative effects (Newquist et al. 2015). Still, to advance end-to-end and global process awareness, the firms established central process mining authorities who aggregate, standardize, and communicate process knowledge across different functions. However, the resulting awareness might still be prone to the observational bias of the streetlight effect and is likely affected by the perception of the central process authority. Alternatively, the management encourages the autonomous, employee-driven development of a shared process understanding by democratizing access to process knowledge.

In addition, our study reveals that the bottom-up driven governance of process mining results in exploratory usage that enables firms to generate awareness on sub- and end-to-end processes iteratively. For this approach to succeed, the technical and conceptual enablement of employees is critical to prepare them for using process mining and to act on its results. Similar observations on the role of education and enablement have been made in recent research on bottom-up driven, people-centric approaches to BPM that aim to include operational employees in understanding and transforming the firm's processes (Bruno et al. 2011; Prilla and Nolte 2012). Our study shows that when employees are enabled, for example, by a CoE, the departments across the firm autonomously adopt process mining to analyze the sub-processes they carry out, which leads them to explore the further end-to-end process context they are embedded in. However, while they develop a shared understanding of the process, unbiasedly without prescribed KPIs to focus on, these efforts lack a coordinated approach to aggregate process knowledge on a global level. Thus, this governance approach causes the awareness resulting from process mining to persist fragmented across functions or end-to-end processes.

Third, while our study provides evidence of how the unbiased, objective transparency created by process mining enables increased process awareness, our study also points to the importance of balancing the social complications of increased transparency, such as employees' fear of surveillance. These findings resonate with previous research in the field of BDA that hints towards the regulatory and organizational backlashes that firms experience through data-driven transparency (Günther et al. 2017; Richards and King 2013). To address these complications, technological measures have been proposed to ensure that data privacy and security are maintained, for example, by anonymizing sensitive data before analyzing it or ensuring restricted access through encryption and authentication (Gahi et al. 2016). On the same note, research on process mining has recently yielded the first advancements toward developing privacy-preserving mining approaches (Mannhardt et al. 2019). Our findings complement these technological measures by shedding light on measures that firms employ to manage challenges resulting from data-driven transparency, such as ensuring democratic and transparent access to analyses or educating employees about data for and functionalities of process mining analyses.

5.4 Practical Implications

In addition, our research has several implications for practitioners. First, by analyzing four different cases of organizational process mining usage, we provide practitioners with an overview of how transparency created by process mining can be leveraged for realizing benefits depending on the organizational and industry context. These reflections can serve as a starting point for discovering valuable process mining opportunities. Second, our findings acknowledge the very real challenge faced by organizations that struggle to increase process mining adoption due to transparency-induced skepticism and restraint in the workforce. We point towards measures to address these concerns that have proven valuable in the context of the four studied organizations. Third, our findings sensitize practitioners to different measures that can be taken to increase organizational process awareness on the sub-process, end-to-end process, or process landscape level. Different measures with different advantages and disadvantages become relevant depending on the process mining governance approach chosen, i.e., a top-down or bottom-up driven scenario.

6 Limitations and Conclusion

To conclude, we acknowledge that our research is subject to several limitations. First, a potential limitation is the retrospective bias of informants regarding their past activities of implementing and using process mining. However, as displayed in Table 2, the emerging mechanisms were triangulated from multiple archival data sources and from the interviews to provide rich descriptions of how the firms' process mining use led to process awareness. Second, we focused our study on the implications of process mining for process awareness as a critical antecedent to process orientation and optimization. Process orientation, however, is a complex phenomenon that requires further organizational changes, such as a process-oriented structure and management. While not within the scope of our study, we consider it a valuable avenue for future research to explore how process mining impacts further dimensions of process management and optimization. For example, our study hints at the implications of process mining for institutionalized organizational structures by establishing process-oriented structures, such as process owner roles. Third, our research is subject to contextual limitations as we studied the emergence of process awareness with regards to medium-sized and large companies with headquarters in Western Europe. While we included a diverse set of companies of different sizes, industries, and process contexts, ranging from analyzing internal production processes to digital customer journeys, our results might be limited in transferability to other settings. For example, national, organizational, and team culture are known to impact a firm's transition towards process awareness (vom Brocke and Sinnl 2011). Therefore, the application of process mining in other cultural or industry contexts, such as the regulated context of public administration, might require alternative mechanisms to foster process awareness.

While process mining presents firms with the opportunity to generate unparalleled transparency regarding their business processes and foster process awareness, organizations still struggle to realize these potentials in practice. This study unravels seven mechanisms that enable firms to generate different forms of process awareness by using process mining, depending on the chosen governance approach. This broadens our understanding of how organizations engage with transparency from process mining, create process awareness and, ultimately, achieve lasting process optimization.

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Appendix B.3 P3: Process Automation on the Blockchain: An Exploratory Case Study on Smart Contracts

Process Automation on the Blockchain: An Exploratory Case Study on Smart Contracts

Julia Eggers
Technical University of Munich
julia.eggers@tum.de

Andreas Hein
Technical University of Munich
andreas.hein@tum.de

Jörg Weking
Technical University of Munich
joerg.weking@tum.de

Markus Böhm
Technical University of Munich
markus.boehm@tum.de

Helmut Krcmar
Technical University of Munich
helmut.krcmar@tum.de

Abstract

While business process automation through information technology has progressed over the last decades, smart contracts have recently emerged as a promising new means of automation. However, in practice, the adoption of smart contract-based automation is in its infancy, raising the question if the technology genuinely offers a unique approach to process automation. Drawing on an exploratory case study of four start-ups, we investigate the potentials for automation that organizations achieve through smart contracts and how smart contracts differ from established automation technologies, such as workflow management systems, enterprise resource planning systems, and robotic process automation. We contribute to the literature on process automation by unveiling transparent and immutable, cross-organizational, and decentralized automation as characteristics that differentiate smart contracts from established automation technologies. Besides, we provide practitioners with an understanding of application scenarios, potentials, and drawbacks of smart contracts for process automation.

1. Introduction

The human drive to eliminate hard manual labor is one of the principal reasons for the rapidly accelerating progress of automation technology. Automating value-creating processes has been ubiquitous during the evolution of humanity. Examples are the invention of the wheel, steam engine, and the computer. The computer significantly increased the transparency, reachability, and automatability of industrial as well as civil processes [1]. Instances of automation can be found everywhere in modern organizations, from an automatically brewed cup of coffee in the breakroom to complex procedures such as robots manufacturing products on an assembly line on the factory floor. However, despite significant technology-based advances in process automation, many firms are confronted with untapped automation potentials as they are struggling to create pervasive transparency and ensure the continuous, integrated, and automated execution of their business processes [2].

Under these circumstances, distributed ledger technology (DLT) and, specifically, smart contracts could hold the potential for the next revolutionary innovation toward extensive automation. DLT describes a distributed database or ledger wherein a group of peers share a copy and jointly scale, manage, and control operations [3]. On top of these ledgers, smart contracts are deployed to automate previously defined transactions if certain conditions in the contract's environment are fulfilled [3]. One prominent commercial application leveraging smart contracts for the supply chain is Everledger, which provides an immutable ledger to automatically track an asset's ownership and transaction history, such as in diamond trade. Instead of a third party manually recording a diamond's origin on paper or entering it into a local database—both methods prone to fraud—the source and transfer of ownership are automatically and permanently recorded on the blockchain using smart contracts. Because the blockchain is immutable, this renders an individual diamond's history not only transparent but also makes it traceable from the mine to the consumer, as well as prevents fraud and theft [4]. Smart contracts, therefore, might provide what established approaches to supply chain automation lack: pervasive, transparent, and distributed data handling for automating processes.

In sum, smart contracts promise a secure and transparent way to automate processes according to predefined rules and without the need to trust a third party to intermediate the transaction. Thus, a growing number of start-ups, for example, in the finance sector, are developing DLT use cases [5]. However,

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according to a recent Gartner report, overall adoption is still in its infancy as incumbents are slow to implement the technology [6].

In light of their slow adoption rate, the question arises: do smart contracts genuinely offer a unique approach to process automation, or are they just the latest hype in the longstanding tradition of process automation technology? Practice demonstrates that most companies would rather trust in established automation techniques than adopt smart contracts. These techniques include, for example, enterprise resource planning (ERP) systems that are used by almost all small- to large-sized companies to integrate business functions, mirror process steps, and automatically execute specified process flows [1]. A second widely adopted substitute is the workflow management system (WfMS). WfMSs focus on controlling process operations concerning predefined operational sequences [7]. Intending to automate the time-consuming, individual steps of a process, robotic process automation (RPA) uses software bots that are programmed to imitate employee behavior by interacting with the front-end of information technology (IT) systems, processing tasks according to predefined rules [8].

Current research lacks a sufficient explanation for how the automation potential of smart contracts differs from that of well-established technologies [9]. Therefore, we are conducting this exploratory case study [10, 11] to unravel what automation potentials organizations might realize by applying smart contracts and if and how smart contracts differ from established automation technologies. Hence, we pose the following two research questions:

1) What automation potentials do organizations realize by applying smart contracts?

2) What are the differences between smart contracts and established automation technologies?

By addressing these two research questions, our exploratory study yields several implications for both research and practice. First, we contribute to the still limited theoretical understanding of the conceptualization and application of smart contracts for process automation. Our study reveals three distinct characteristics that differentiate smart contracts from established automation technologies while acknowledging the challenges that complicate the adoption of smart contracts in practice. Second, we provide practitioners with an understanding of application scenarios, potential benefits, and the drawbacks of smart contracts for process automation.

2. Theoretical Background

To contrast smart contracts with dominant process automation technologies, we first synthesize previous findings on DLT and smart contracts and present an overview of the advantages and disadvantages of conventional techniques for process automation, such as ERP systems, WfMSs, and RPA.

2.1. Distributed Ledger Technology

DLT is a type of database maintained by a peer-to-peer (P2P) network of nodes, which scale the database up and avoid the development of any single point of failure [12]. Peers can be distributed geographically as well as institutionally; moreover, each peer has a copy of the ledger [5]. The primary purpose of DLT is to enable untrusted peers to interact without the need for a trusted third party to mediate the interaction [12]. Therefore, a trusted ledger is based on two fundamentals. First, cryptographic means are applied to ensure immutable data on the ledger [5, 12]. Immutability is achieved through functionality such as digital signatures and fingerprints, taking the form of hash functions to ensure data validity. Second, peers agree on a particular state of the ledger to sustain a consistent data state [5, 12]. DLT, in general, encompasses a variety of implementations, the arguably most popular of which is the blockchain, which enables the realization of smart contracts [3].

2.2. Smart Contracts

Smart contracts are, in essence, programmed if-then-else conditions [13]. A smart contract can be a digital version of a contractual agreement between different parties or a relationship enforced by code, without any underlying contractual obligations or rights [3]. Even though the idea of the smart contract was already proposed by Szabo [14] in 1996, the realization of such a construct was not feasible at the time [13, 15]. Today, smart contracts are realized as decentralized, trusted, and shared code deployed on the blockchain, such as Ethereum or Hyperledger Fabric [16]. In this paper, we refer to the definition of smart contracts by Tapscott and Tapscott [15] as "*computer programs that secure, enforce, and execute settlement of recorded agreements between people and organizations*". The computer program specifies the necessary predefined rules and ensures the automated execution of certain operations when corresponding trigger conditions are satisfied without the involvement of intermediaries [16]. The technological basis of smart contracts enables various potential use cases, ranging from product traceability along the supply chain to ensure regulatory compliance to defeating counterfeit products and fraud in industries such as healthcare, food, and energy [5].

One particularly promising application for smart contracts is the automation of business processes. Since smart contracts guarantee the automatic and transparent execution of predefined rules, they enable human judgment to be taken out of the equation [3]. An example is the automated handling of insurance policies deployed on the blockchain in the form of smart contracts. Once an insurance policy, such as a car insurance policy, is deployed as a smart contract, the smart contract automatically queries external sources for any events that might cause the filing of an insurance claim, for example, a crash that is detected by sensors in the car. In case such an event is detected and meets the predefined conditions, the smart contract automatically executes the terms of the insurance and issues the policyholder's payout. Therefore, the smart contract eliminates the need for trusted third parties and takes over the mediator role, directly connecting the parties in an inter-organizational context [17].

While smart contracts are promising for process automation, previous research has drawn attention to several challenges related to the understanding of and trust in the technology. First, for organizations to trust smart contracts, knowing how a specific smart contract is designed is necessary. However, it is difficult for people without technical expertise to read and therefore understand the source code of a smart contract [13]. Second, transparency as an essential DLT property also raises privacy concerns. For example, financial transactions are often seen as highly confidential and could, therefore, affect the adoption of smart contracts [18]. Third, the trustworthiness of the external data sources queried by smart contracts needs to be assured, for example, through a trusted third party [13]. Finally, the immutability of smart contracts is a challenging aspect for organizations, especially during the development and deployment phase, since errors cannot simply be erased with software updates [16].

2.3. Enterprise Resource Planning Systems

While organizations rely on various IT systems to support their business processes, such as customer relationship management or supply chain management systems, ERP systems arguably emerged as one of the most prominent and widespread IT systems used in almost any organization to manage resources and support business processes [1]. Thus, our analysis exemplarily focuses on ERP systems. Due to the widespread use and improvement of ERP systems over the years, they now offer pre-built, best practice-based automation options to automate standard processes such as accounting or order procedures. Adopting an ERP system thus offers an organization the opportunity to transfer tacit knowledge on process automation. One example is the University of Nebraska, which implemented an ERP system to improve accounting, inventory, and purchasing processes. After implementing the new system, a standardized, rule-based, centrally controlled procedure offered inherently by the system design was adopted for purchasing processes [1]. However, inheriting system-induced best practices and transferring tacit knowledge on process automation requires the adopting organization to adapt or omit existing processes significantly. Such enforced adoption of new, partly automated processes might stir conflict in the workforce that can be time-consuming and difficult to resolve [19]. In addition, ERP adoption and customization are usually associated with substantial implementation costs [1].

ERP systems not only provide pre-built automation solutions but also offer the data foundation necessary to improve existing automation. As data storage in a single location requires the enforcement of strict database rules for all data, including type, form, and accessibility, analytics technology can be deployed upon the vast amount of standardized data available in ERP systems. For example, analytics algorithms based on pattern recognition can automatically switch running processes to alternative routines in case of an erroneous process execution [20]. At the technical level, however, the administration and management of data from various sources require investment in the infrastructure and resources required to transform data into valuable insight [20].

2.4. Workflow Management Systems

Workflow management describes the control of document operations in terms of roles and responsibilities, associated access rights, and the operational sequence of document editing [21]. In general, WfMSs bear great potential for rule-based, low-level process automation. Based on predefined workflows modeled by the user, the system automatically ensures document consistency and availability within a process, automatically triggers sub-process parallelization if suitable, and automatically executes the steps of the process following predefined business rules [21]. In addition, WfMSs are extendable to interact with sub-systems or other WfMSs across company borders through web services or middleware, which is a key factor for automating distributed business processes [19, 22]. In recent years, WfMSs have been augmented with distributed data tracking functionality, such as radio frequency identification (RFID) sensors, which allow, for example, the granular tracking of items in the manufacturing workflow. This approach is similar to smart contract-enabled distributed data tracking [23].

However, WfMSs require continuous time- and resource-consuming analyses to ensure their effectiveness. Such analyses include testing to ensure the predictability of workflow behavior, testing to eliminate redundancies and deadlocks, and data usage analysis to prevent fraud [24]. Accordingly, dynamic changes in workflows at runtime pose a significant challenge as they contradict system predictability and controllability [21]. Besides, reflecting actual processes in the WfMS can be problematic since various process variants usually coexist. Because WfMSs are not designed to represent this complexity, an oversimplification of the organizational process dimension results in either WfMS inflexibility or exceeded liberality, thereby deteriorating the effectiveness of the system [7]. Finally, associating large amounts of data, for example from RFID, potentially increases the complexity of integrating WfMSs with other enterprise information systems, thus increasing the amount of time required to develop, test, and maintain process automation [23].

2.5. Robotic Process Automation

RPA has gained momentum in recent years as a lightweight, easy-to-configure IT solution that enables organizations to automate business processes [8]. To achieve process automation, RPA leverages software bots that imitate human-system interactions [25] without requiring the underlying system infrastructure or code to be changed [8]. An RPA bot is designed to access the system through the user interface, similar to how an employee would use an IT system. Then, the bot processes the tasks according to predefined rules and delivers the data to subsequent systems [26]. Tasks that are particularly suitable for automation using RPA are often referred to as "swivel chair" processes [8], for example, when an employee takes electronic input from one system, processes it according to predefined rules, and then enters the data into another system. RPA aims to relieve employees of monotonous tasks, thereby increasing their job satisfaction as they become free to focus on more complex and creative tasks [8]. In addition, overall productivity and product and service quality increase due to the faster and less error-prone task execution of bots [26]. Although RPA bears significant automation potential, its economically valuable application remains limited to rule-based processes that are time-consuming yet unlikely to yield unexpected events [25]. The strong dependency on predefined patterns excludes the application of RPA for tasks that require common sense, a creative approach, or exception handling [8]. Further technical limitations are due to the underlying IT systems that are designed for human utilization. Thus, they may not be able to cope with bot speed, leading to errors and process failures [8].

While there are various technologies available for realizing process automation, it should be noted that scholars have long debated whether an increase in process performance is not only able to be achieved by automating processes through technologies such as ERP systems, WfMSs, or RPA bots but also by radically reengineering or obliterating processes [27]. The basic assumption is that the automation of ineffective or cumbersome processes might result in rather undesirable outcomes, such as slow, erroneous business processes. While we agree with the importance of comprehensive business process management and reengineering as an antecedent to process automation, we focus our study on the implementation phase of process automation as it is enabled by different technologies.

3. Methodology

Sampling Strategy. Due to the recent emergence of smart contracts as a field of research and their scarce application in practice, we chose to conduct an exploratory case study [10] drawing on various cases. The case study design allowed us to study the contemporary phenomenon of the smart contract as an automation tool in its organizational context. Furthermore, the analysis of multiple cases ensured robust findings using literal replication [10]. We selected four organizations that met the following criteria: (1) offering a product based on smart contracts and (2) using smart-contract technology to automate part of the value generation process. The four organizations chosen were operating as start-ups in the real estate, insurance, logistics, and security industry, respectively (see Table 1).

The first case is *ImmoCorp*, a Switzerland-based start-up founded in 2018 operating in the real estate market. *ImmoCorp* uses smart contract-based technology to create tokenized, digital twins of properties, meaning that buildings are represented by a defined number of digital tokens that could then be bought or sold through the *ImmoCorp* platform. Properties are sold in "crowdsales," referring to multiple buyers jointly acquiring the real estate. After the acquisition, owners can use the platform to vote on matters concerning their property.

Second, we chose *InsurCorp*, a German start-up founded in 2016 that offers a smart contract-based platform for decentralized insurance products. For our study, their parametric flight delay insurance was of particular interest since this application enables the automated and decentralized pricing, underwriting, and processing of insurance policies for flight delays.

The third case is *LogiCorp*, a Switzerland-based start-up founded in 2016 that uses smart-contract technology in combination with sensors to automatically monitor the end-to-end shipment of products prone to strict temperature regulation.

Fourth, we included the start-up *SecurCorp*, founded in 2017 in the US that offers a decentralized marketplace for threat intelligence using smart contracts. The marketplace automatically connects anti-malware providers with end customers to provide threat detection products aligned with their specific needs.

Data Collection. To ensure construct validity [10], we used multiple sources of evidence, including semi-structured expert interviews [28] and archival data, such as case studies, product demos, and newspaper articles. Our interview questions focused on three areas of inquiry: how the firm uses smart contracts, why they use smart contracts to automate part of the value generation process, and how smart contracts differ from alternative automation techniques available. To ensure reliable results, we maintained a chain of evidence through a case database [10].

Data Analysis. We engaged in explanation building [10] as an analytic technique, wherein we continuously iterated between initial explanatory propositions and the findings from the cases to explain why organizations chose smart contracts as automation technology. To provide for external validity, we conducted a cross-case analysis to demonstrate the transferability of results from the within-case analysis to a context outside of the specific case scenario [11].

Table 1. Overview of case studies

Company	Industry	Interviews	Archival	Demo
ImmoCorp	Real Estate	2	5	Yes
InsurCorp	Insurance	1	5	Yes
LogiCorp	Logistics	1	6	No
SecurCorp	Security	2	5	Yes

4. Results

Our study reveals automation by disintermediation and automation by reducing manual process steps as key automation mechanisms by smart contracts.

4.1. Automation by Disintermediation

First, smart contracts enable firms to design and automate processes by skipping intermediaries. In the case of *InsurCorp*, applying smart contracts allowed the organization to fundamentally change insurance processes. As in the case of flight delay insurance, insurance services usually rely on a complex process involving multiple actors, such as insurance brokers, who negotiate the policy with potential policyholders, and the underwriter that manages the cash flows. *InsurCorp*, however, uses smart contracts to skip brokers and even the insurance company, so the customer only interacts with the smart contract. The insurance policy and all related assets and processes, including pricing, underwriting, issuing, and claim settling, are now deployed as a smart contract with DLT. Triggered by external events, such as the delay of an insured flight, a smart contract automatically executes predefined steps. In the event of a claim, the smart contract automatically pays out the insurance sum to the policyholder, skipping the intermediating insurer, as an *InsurCorp* employee described:

"[Customers] do not have to ask anyone about the money, they are not dependent on an insurance company whether this payout happens or not, but it happens automatically, solely based on data. [...] There is no middleman anymore; no one is mediating between the insured parties and gets paid to manage these cash flows."

However, due to strict regulations in specific industries, such as the real estate market, it is currently impossible to eliminate all intermediaries with smart contracts. In the case of *ImmoCorp*, the platform must verify each new user using third-party identification services. In addition, each "crowdsale" of a tokenized property on the *ImmoCorp* platform requires an off-chain notary to approve the sale. Nevertheless, the smart contract-based platform eliminates the need for a bank to act as an intermediary to facilitate the transaction and manage cashflows. A user is only required to own a wallet that represents a public and private key used to receive or spend cryptocurrency on the blockchain. When properties on the platform are sold in "crowdsales," the smart contract ensures that all payments are automatically collected and stored on the blockchain. After a predetermined sales period expires, the "crowdsale" is closed, and, in case the desired price has been achieved, an off-chain notary approves the sale. Next, the smart contract pushes the automatic transfer of the sum paid to the seller(s), while ownership of the property automatically changes. Therefore, users and the platform become independent of banks and real estate agents, providing them with more flexibility in buying and selling tokenized properties, as described by a technology expert from *ImmoCorp:*

"You can sell [the tokens of a property] again the next day if you want to, and you have everything under control yourself. You do not need middlemen;

you do not have to see a bank advisor or a lawyer; you can do it yourself from home."

By eliminating the bank as an intermediary, the payment procedure for a property is automated from end to end. Instead of issuing a wire transfer that requires one bank to allocate the money from the buyer's bank account to the seller's account—sometimes prompting the conversion of currencies—the money is directly and automatically transferred via the smart contract.

Drawing on smart contracts to automate end-to-end cross-organizational processes enables *SecurCorp* to dissolve formerly rigid company boundaries. *SecurCorp* leverages smart contracts to automate transactions in the global anti-malware marketplace using a common cryptocurrency as the means of payment. Based on the Ethereum blockchain, the smart contract-based application provides a shared infrastructure for customers and providers from the anti-malware industry to interact directly and automatically exchange documents, assets, and information across company borders. Therefore, the automation of transactions becomes independent of the customer's and provider's individual local infrastructures but relies entirely on the smart contract to function as a shared infrastructure that can support an end-to-end transaction. Consequently, the payment procedure is automated through smart contracts. Previously, customers manually paid the provider in their local currency via wire transfer, possibly requiring a currency conversion by an intermediating bank. Now, the smart contract can automatically transfer cryptographic assets between the customer and provider according to predefined rules, as an employee of *SecurCorp* explained:

"*We want to be a worldwide marketplace. Furthermore, if you are not using some form of a fixed token, then you have to deal with fiat in every country where people want to participate. So instead of us dealing with fiat, we are dealing with a single token [and so] we need a smart contract.*"

4.2. Automation by Reducing Manual Process Steps

Smart contracts provide new means for automated and secure data tracking and distribution, thereby automating process steps that otherwise need to be performed manually. *LogiCorp* uses these properties to automatically and reliably track the supply chain of temperature-sensitive pharmaceuticals. Regulations require that temperature-sensitive products be monitored during delivery and that temperature data be distributed to the vendor and buyer upon shipment to ensure regulatory compliance. Formerly, tracking and distributing temperature data was a highly labor-intensive process involving the manual programming of temperature sensors and the manual collection, analysis, and redistribution of data from individual sensors. With smart contracts, each shipment persists on the blockchain, containing the predefined permissible temperature range and an identifier for the temperature sensor placed in the shipment. This process ensures that the logged temperature data is immutably stored on the blockchain. Upon delivery, the sensor is scanned, which triggers the smart contract to automatically analyze the data and send a report to all involved stakeholders. Smart contracts enable faster automated monitoring of the supply chain, as a founder of *LogiCorp* explained:

"*It was a cumbersome procedure, and it relied on much work between sender and receiver and came with time delays. But now being able to know [the temperature data] immediately upon arrival prevents shelving of compromised goods and keeps senders automatically aware of any challenges they are having in the supply chain.*"

SecurCorp leverages smart contracts to automatically execute predefined actions that enable automated matching of service providers and customers in the anti-malware market. Formerly, customers either relied on per-seat license models to acquire a single anti-malware package from incumbent software providers or directly approached specialized anti-malware providers for specific problems. By contrast, the *SecurCorp* platform creates a marketplace in which customers are able to submit a digital artifact to be checked for malware by different service providers. The smart contract-based platform then automatically distributes the request to anti-malware service providers, according to their predefined capabilities, that are registered on the platform. These service providers offer specialized software that automatically first analyzes the received artifact and then replies to the customer with a verdict (i.e., whether the artifact is malicious or benign) and an assessment regarding their verdict's certainty. Also, a synthesized recommendation based on a majority vote is sent to the customer that is recorded on the blockchain, allowing transparency on how anti-malware providers perform over time. Therefore, the smart contract automatically facilitates the matching of customer and provider so that customers no longer need to search for one suitable security expert manually. Instead, they automatically receive an assessment from multiple experts, as described by a *SecurCorp* employee:

"*[T]he smart contracts are doing all of the transactions between the people submitting the files* *and the people analyzing the files. Moreover, [the smart contract is] recording the results. So, the function of the smart contract is really to allow the people who have a file to submit it automatedly*."

5. Discussion and Conclusion

There are three key differences when comparing smart contract-based process automation with established automation technologies, such as ERP systems, WfMSs, and RPA.

5.1. Transparent and Immutable Automation

First, we observe that smart contracts offer a transparent and immutable manner for automating processes due to their underlying blockchain technology. While immutability on the blockchain is not new, this combination with automation enables companies to automate business processes according to predefined, unchangeable rules. As in the case of *InsurCorp*, the rules for automated insurance payout are specified in the smart contract available on the Ethereum blockchain. Therefore, the insurance policy is fully transparent to the customer. The smart contract and the subsequent insurance payout, which cannot be changed once signed, are publicly available and accessible to everyone. The transparency and guaranteed immutability of automation rules are likely to increase users' trust in smart contract-based automation. Research has long shown that transparent process automation, referring to users knowing the inner logic and rules of the automated system, fosters a higher level of user trust and human-automation task performance [29]. Building trust in financial transactions through increased transparency could be one reason for organizations to apply smart contracts in the future, for example, to automate trade financing. There are examples in practice already, such as the case of a large Australian bank that advanced itself as one of the first financial institutions to apply smart contracts to automatically and transparently process invoice financing documents [30].

On the contrary, for established process automation technologies like WfMSs, RPA, and ERP systems, there is no guarantee of such transparency. Automation rules might not be clear and accessible to all users of the system. Instead, they are known only by system administrators or programmers [31], leaving most system users unaware of the underlying automation procedures. This effect intensifies as the automation rules in WfMSs, ERP systems, and RPA bots are modifiable and, thus, can be altered without all users being aware of the changes [31]. However, the option of changing process automation declarations after being deployed leaves room to adapt to changing environmental conditions, such as new regulatory requirements or varying customer expectations [21].

In this regard, smart contracts are limited in their ability to adapt to shifting process requirements. Because immutability is a core concept of the blockchain, once a smart contract is deployed on the blockchain, it cannot be changed. Instead, desired changes must be deployed as a new smart contract, which then needs to be referenced by all stakeholders while the previous smart contract is simultaneously disabled [16]. This complex updating procedure results in increased tension arising between inflexible process automation and quickly changing business conditions. We observed this complication at *ImmoCorp*, which is subject to the changing regulations of the real estate industry. Therefore, the firm was required to develop a complex proxy-based architecture workaround to enable frequent changes in the smart contract's automation rules.

In conclusion, compared to established automation technologies, smart contracts offer a more transparent means for process automation. The underlying logic is guaranteed to be both reliable and accessible to all users. This increased transparency is likely to increase user trust in automated transactions. As a downside, automation with smart contracts suffers from rule rigidity and the inflexibility to adapt to changing requirements.

5.2. Cross-Organizational Automation

Second, organizations achieve end-to-end automation of cross-organizational processes using smart contracts. As observed in the case of *SecurCorp*, smart contracts provide the necessary company-spanning, decentralized infrastructure that is required to connect customers' and providers' local infrastructures. A centralized authority does not maintain the infrastructure. Therefore, several organizations can cooperate without the need to agree on a third-party provider [17]. Building on the blockchain, cross-organizational automated transactions such as document and asset exchange become feasible through the intermediating actions specified in the smart contract. In addition, the automation rules are transparent to all involved parties, which can promote increased trust in the automated process itself. These findings are consistent with a previous study that demonstrated that a blockchain-based system could facilitate cross-organizational process management and automation by providing a common and transparent infrastructure [17]. Therefore, one reason why organizations choose smart contracts might be to automate processes across different systems and company boundaries transparently. One promising area of application is the healthcare industry, which is today characterized by many actors and systems being necessary to execute healthcare services, such as filling a prescription. Smart contracts are expected to provide the required, low-cost infrastructure to automate transactions between healthcare providers, health insurance companies, and patients [32].

Still, cross-organizational process automation is considered a complex endeavor, and there is consensus that not all automation technologies are suitable. RPA, for example, is not considered to be a technological fit for cross-organizational end-to-end process automation. Instead, RPA is designed as a tool operating on the user interface of IT systems with the goal of intra-organizational, low-level automation aimed at individual steps of a process [26]. ERPs and WfMSs, however, can be applied by organizations to realize cross-organizational process automation. Although used at the individual enterprise level, these systems can be integrated between organizations at the infrastructure level, drawing on, for example, middleware or web service technologies to automatically exchange data across company boundaries [19]. However, implementing the solutions raises technological and governmental challenges such as agreeing on shared infrastructure providers [17], ensuring data flow transparency, and deciding on responsibility for data entry and updates [19]. In addition, concerns regarding data privacy and security become essential [33]. Connecting ERPs or WfMSs between organizations bears the risk of unintentionally sharing sensitive data, such as employee- or finance-related information, with another organization [22]. Therefore, firms perform complex data anonymization or filtering procedures [33] before sharing data.

Data privacy also plays a significant role in smart contract-based process automation. The example of *ImmoCorp* indicates that the procedural transparency offered by smart contracts poses the risk of storing and sharing sensitive transactional data such as the name and address of real estate investors with all parties that have access to the blockchain. *ImmoCorp* is, therefore, relying on a hybrid approach in which sensitive information is stored in off-chain databases, and only the storage address persists on the blockchain. These findings support previous work arguing that the lack of data privacy is a drawback of smart contacts [18].

In conclusion, companies realize cross-organizational end-to-end process automation using smart contracts as a shared automation infrastructure that connects organizations' local IT systems according to transparent rules. Similarly, cross-organizational process automation can be achieved by integrating WfMSs or ERP systems between company boundaries employing web services or middleware systems. However, these types of automation are not necessarily transparent to all stakeholders and often depend on trusting a third-party infrastructure provider. Besides, there is the risk of unintentionally sharing sensitive data between companies through end-to-end process automation, independent of the chosen technology.

5.3. Decentralized Automation

Lastly, organizations leverage smart contracts to enable decentralized process automation independent of intermediaries or third-party providers. Disintermediation is a frequently cited advantage of smart contracts [16]. In the context of process automation, it allows for faster process execution by automating or skipping process steps that were formerly related to intermediaries. The example of *InsurCorp* demonstrates how smart contracts eliminate the need for an insurance company to act as an intermediary since the insurance policy and all related coordinating processes are deployed as a smart contract on the blockchain. Therefore, both customer-facing processes, such as insurance payouts, and back-office processes, such as flight delay checks, are performed automatically and without a third-party coordinating or executing the transaction. For this reason, *InsurCorp* claims to provide a faster payout process than incumbent insurance companies.

In addition, neither stakeholders nor third parties need to host the shared infrastructure since the blockchain is designed as a decentralized P2P network. The decentralized infrastructure also ensures that the stakeholders no longer need to trust a potentially unknown third-party provider who controls the automation infrastructure. Instead, control of the blockchain-based infrastructure is distributed among all transaction stakeholders. In contrast, WfMSs, RPA, or ERP systems provide a centralized approach to automation that usually requires the stakeholders to trust a third party, such as consultants, vendors, or IT departments, to build and maintain the corresponding infrastructure [34]. Especially in the insurance industry, smart contracts appear to be a promising technology for not only decentralizing and automating processes but also facilitating new business models independent of intermediary organizations. Today, this trend can be observed in a growing number of start-ups offering smart contract-based insurance products, ranging from maritime freight insurance to pet or unemployment insurance [35]. At the same time, incumbent insurers face the challenge of adopting smart contracts that inherently pose the risk of rendering them obsolete by taking over the insurance company role [36].

However, successfully leveraging smart contracts for decentralized automation depends on the collaboration of all stakeholders, including customers, vendors, and logistics providers. Persuading stakeholders to use smart contracts can be challenging because doubts and misconceptions about the new technology prevail. *LogiCorp* was challenged in convincing supply chain stakeholders, such as pharmaceutical producers and logistics providers, to engage in supply chain process automation using smart contracts. Stakeholders were insecure about the technical functionality and data security, and only after *LogiCorp* delivered proof of concept on the implementation of smart contracts was a consensus reached. Similar concerns can also be currently observed in the emerging RPA market, as companies are still skeptical about the functionality and benefits of RPA-based process automation [26]. In contrast, established automation technologies with a high market share, such as WfMSs and ERP systems implemented by well-reputed vendors, are perceived as rather trustworthy and useful [34].

Overall, organizations choose smart contracts to achieve efficient, decentralized process automation that is no longer dependent on a centralized infrastructure or requires trust in intermediaries. However, contrary to established automation technologies, such as ERP systems and WfMSs, firms still struggle to convince process stakeholders to adapt smart contracts-based automation due to the technology's novelty.

5.4. Limitations and Conclusion

Even though smart contracts promise a secure and efficient way to automate business processes, in practice, the adoption rate is rather slow [9]. Therefore, our study set out to explore what automation potentials organizations might realize by applying smart contracts and how smart contracts differ from established automation technologies. By drawing on four case studies, we demonstrated that organizations implement smart contracts to achieve transparent, immutable, cross-organizational, decentralized process automation.

However, our study is subject to several limitations. First, by studying only organizations that have implemented smart contracts to achieve process automation, our study does not cover the perspective of firms that have rejected smart contracts and opted for alternative automation technologies. While our study provides a primary exploration of the characteristics that make smart contracts a valuable automation solution, we suggest that future research investigate the challenges of implementing smart contracts along with reasons for choosing alternative automation technologies. Second, our research was designed as a highly exploratory endeavor due to the novelty of the technology and the sparse extant research on its application. Therefore, we investigated four start-up companies from a variety of industries taking a qualitative approach, which provided insights regarding the still unexplored reasons that firms automate processes using smart contracts. Still, we encourage scholars to systematically further knowledge on the benefits and challenges of smart-contract applications for process automation, specifically for incumbent firms that usually maintain legacy systems and complex processes.

In light of the low adoption rate of smart contracts in practice, especially for incumbent firms, the question arises if smart contracts are only the newest hype in a longstanding tradition of process automation technologies. Our study shows, however, that smart contracts offer distinct automation opportunities compared to established automation technologies. Smart contract-driven automation enables organizations to eliminate formerly required intermediaries while increasing stakeholder trust in automation through transparent and unchangeable automation rules recorded in the smart contract. In addition, the deployment of smart contracts on the blockchain provides a company-spanning automation infrastructure that is independent of a third-party provider—in contrast to ERP, WfMSs, or RPA providers—but instead jointly maintained by all process stakeholders. However, smart contracts should not be considered a universal approach to automation. Today, their implementation is challenged by privacy concerns due to the complete transparency of the blockchain, by inflexibility due to the blockchain's immutability, and by the skepticism of stakeholders who are slow to adopt the new technology.

6. References

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Appendix B.4 P4: Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development

Supporting Subject Matter Experts as Developers: Towards a Framework for Decentralized Robotic Process Automation Development

Julia Eggers
Technical University of Munich
julia.eggers@tum.de

Judith Wewerka
Ulm University
judith.wewerka@uni-ulm.de

Altus Viljoen
Technical University of Munich
altus.viljoen@tum.de

Helmut Krcmar
Technical University of Munich
helmut.krcmar@tum.de

Abstract

Robotic Process Automation (RPA) has emerged as promising automation technology in recent years. Firms seize RPA for fast and cost-efficient low-code process automation implemented and maintained decentrally in the business units by subject matter experts (SMEs) without IT development experience. However, decentralized RPA projects are reported to frequently fail and be prone to challenges as SMEs struggle to meet their new roles and responsibilities, such as developers or testers. Yet, research lacks an understanding of how challenges related to SMEs' roles and responsibilities unfold and how to address these challenges when executing decentralized RPA projects. To this end, our study employs a Design Science Research approach, drawing on literature and 14 expert interviews, to (1) systematically synthesize the challenges related to SMEs' roles and responsibilities and (2) derive a software development framework for supporting SMEs in their new roles and responsibilities in decentralized RPA projects. Thus, our study contributes to RPA and low-code development research and provides SMEs with guidelines to navigate decentralized RPA projects in practice.

Keywords: Robotic Process Automation, Software Development, Low-Code, Design Science Research.

1. Introduction

As international competition pressures firms to achieve fast and cost-efficient operations, they increasingly embrace digital technologies to support and automate their business processes (Wanner et al., 2019). In this light, Robotic Process Automation (RPA) emerged in recent years as a technology for firms to automate tedious, time-intensive manual processes at the task level with software robots (Hofmann et al., 2020)—so-called bots—, thereby enabling firms to reduce process costs, increase efficiency and speed, and achieve higher customer satisfaction (Flechsig et al., 2019). To this end, RPA provides firms with the tools to configure bots that imitate human employees' manual work by interacting with different systems on the user interface (Lacity & Willcocks, 2016a). Accordingly, RPA has attracted the interest of firms of various industries and sizes and is, therefore, considered to be "*on its way to mainstream*" (Shetty, 2018). Gartner predicts that 85% of large firms worldwide will have adopted RPA by the end of 2022, and its significance for companies is only expected to grow (Shetty, 2018).

RPA is particularly interesting for organizational use because it is a low-code automation solution (Bock & Frank, 2021). In contrast to traditional process automation, which requires the (re-)programming of systems and is led and implemented by the IT department (van der Aalst et al., 2018), RPA is based on a low-code approach that does not require any changes in the underlying IT systems (Osmundsen et al., 2019). Thus, it can be implemented in the business units by subject matter experts (SMEs) without IT background, also referred to as "citizen developers" (Bock & Frank, 2021). Previous research highlights that decentralized RPA implementation with local ownership allows firms to better benefit from RPA, for example, by fostering innovative applications, leveraging the process knowledge of SMEs, and quickly addressing business units' needs (Bygstad, 2017; Osmundsen et al., 2019).

However, RPA projects are prone to high failure rates, reported as 30 to 50% (Ernst & Young, 2016), and studies indicate that decentralized RPA projects are accompanied by challenges (Noppen et al., 2020; Osmundsen et al., 2019). For example, citizen developers without IT expertise and with low or no support from the IT department have trouble understanding the capabilities and requirements of RPA (Lacity & Willcocks, 2016b). Additionally, SMEs now have to balance traditional operational responsibilities with unfamiliar RPA-related responsibilities, such as development, analysis, testing, and maintenance (Osmundsen et al., 2019).

Drawing on these observations, we conclude that decentralized RPA development and the resulting new roles and responsibilities of SMEs yield considerable organizational and technical challenges that firms need to address for successful decentralized RPA projects.

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However, as RPA is still a young technology, research lacks a systematic understanding of how challenges related to the roles and responsibilities in decentralized RPA projects unfold and how to address them in an overarching, systematic development framework (Syed et al., 2020). Instead, most studies thus far have focused on establishing frameworks to guide the initialization and scaling of RPA on the organizational level (Herm et al., 2020; Syed et al., 2020) or for specific industries (Huang & Vasarhelyi, 2019), while managing individual RPA projects with the different roles and responsibilities inherent to decentralized RPA development remain largely unaddressed. Thus, we pose the following research question:

What is a software development framework for decentralized RPA projects supporting SMEs in their roles and responsibilities?

To this end, we follow a Design Science Research (DSR) approach (Hevner, 2007). Drawing on literature and 14 expert interviews, we (1) systematically synthesize the challenges related to SMEs' roles and responsibilities in decentralized RPA projects (i.e., insufficient understanding of RPA capabilities and requirements, incomplete or ambiguous analysis and documentation of as-is processes, lack of IT development knowledge and experience, maintenance responsibilities in the business unit, balancing RPA developer and operational roles, administrative overhead) and (2) develop a software development framework for decentralized RPA projects supporting SMEs in their roles and responsibilities. As a result, our study contributes to research on RPA and low-code development and provides practitioners with a framework to navigate decentralized RPA development.

2. Related Work

2.1 Robotic Process Automation (RPA)

RPA is a software-based solution to automate business processes with a bot that interacts with information systems on the user interface and is configured to execute work that humans performed manually (Lacity & Willcocks, 2015; van der Aalst et al., 2018). Tasks well suited for RPA are repetitive, rule-based, and processed in high volume (Hofmann et al., 2020), such as transferring data from input sources to systems of record, like Enterprise Resource Planning (ERP) systems (Lacity & Willcocks, 2016a). As a result, employees are relieved of time-consuming, repetitive tasks and can focus on value-adding activities (Asatiani & Penttinen, 2016).

RPA is considered a low-code automation technology, running on the user interface of systems without requiring changes in the underlying programming logic. Consequently, no programming skills are necessary for developing RPA (Lacity & Willcocks, 2016a). Instead, bots are configured on low-code platforms offered by RPA vendors (Hofmann et al., 2020). These platforms enable the "*rapid application development, deployment, execution and management [of bots] using declarative, high-level programming abstractions*" (Bock & Frank, 2021, p. 733), such as drag-and-drop features for citizen developers without programming skills to assemble automated workflows (Bock & Frank, 2021).

Consequently, firms often organize RPA projects in a decentralized approach outside the IT department, with business units holding RPA ownership and citizen developers implementing and maintaining bots (Osmundsen et al., 2019). In addition, an RPA Center of Excellence (CoE) might provide technical support, e.g., by offering code reviews or implementation guidelines (Noppen et al., 2020). Thus, decentralized RPA projects contrast traditional automation projects led and executed by IT professionals (Bygstad, 2017).

Previous research highlights that decentralized RPA projects based on local ownership allow firms to better benefit from RPA, e.g., by fostering innovative applications, leveraging SMEs' process knowledge for bot development, and quickly addressing automation needs (Bygstad, 2017; Osmundsen et al., 2019).

Yet, studies indicate that the decentralized RPA approach is accompanied by challenges (Noppen et al., 2020; Osmundsen et al., 2019). For example, SMEs have to adopt unfamiliar roles, such as developers, analysts, and testers, while struggling to balance their operational and RPA-related responsibilities (Osmundsen et al., 2019). In addition, citizen developers without IT expertise and with little support from the IT department experience time-consuming development and maintenance (Osmundsen et al., 2019).

Drawing on these observations, we argue that SMEs' new roles and responsibilities, such as RPA project managers, analysts, citizen developers, testers, and users, yield considerable organizational and technical challenges for decentralized RPA projects. However, research still lacks a systematic understanding of how these role-related challenges unfold and how they could be addressed using an overarching, systematic development method (Syed et al., 2020) supporting the different roles and their responsibilities inherent to decentralized RPA projects.

2.2 Frameworks for Decentralized RPA Development

With the rising popularity of RPA in practice, questions arise on how to successfully organize and support decentralized RPA development (Syed et al., 2020). Even though research yielded several RPA development frameworks (see Herm et al. (2020) for a recent review), most of the frameworks do not focus on the decentralized approach and neglect the roles of SMEs by either assuming that RPA projects are executed by IT professionals/ a shared service function or omitting questions around roles and responsibilities (for example, Enríquez et al. (2020), Rutschi and Dibbern (2020), Cewe et al. (2018)). However, a few frameworks acknowledge decentralized RPA development but still fall short of specifying the roles and responsibilities inherent to decentralized RPA projects. We give a short overview of these frameworks in the following (see Table 1).

Flechsig et al. (2019) develop a framework based on the established Business Process Management (BPM) lifecycle to guide firms in combining RPA with BPM to ensure that process discovery, optimization, and monitoring are integrated into RPA development. However, while they acknowledge that the development of bots is "*almost completely independent of IT staff*" (Flechsig et al., 2019, pp. 6-7), their framework does not provide specifications of the roles and responsibilities of SMEs involved in RPA development.

Herm et al. (2020) derive a framework for supporting firms in initiating and scaling RPA projects on the organizational level. Their findings show how firms can explore and incorporate RPA into the firm, e.g., by establishing an RPA CoE. Yet, questions on the level of individual RPA projects, including the organization of roles and responsibilities, remain open.

Huang and Vasarhelyi (2019) provide a framework for developing RPA bots for auditing. They guide auditors to create their own bots and "*build a [RPA] program in-house*" (Huang & Vasarhelyi, 2019, p. 5). However, even though their work considers SMEs as citizen developers, there is a lack of focus on what roles and responsibilities to include and manage in decentralized RPA projects.

Noppen et al. (2020) develop a framework to guide firms in initiating and scaling maintainable RPA projects. They provide rich insights into how firms decentrally develop RPA and ensure structured RPA governance and maintenance, e.g., by establishing a CoE and institutionalizing development standards. Still, the framework lacks consideration of the level of individual RPA projects and how to manage roles and responsibilities in decentralized RPA projects.

Syed et al. (2020) derive guidelines based on a structured literature review to support firms in adopting RPA on the organizational level and ensuring scaling and long-term success. At the same time, they acknowledge that research lacks a rigorously developed framework for guiding RPA implementation projects and that the implications of RPA projects on the workforce, such as SMEs, are yet to be understood.

In sum, research has yielded several frameworks for decentralized RPA development. Most frameworks focus on introducing and scaling RPA on the organizational level, while only a few guide RPA development on the project level. Thus, the specific development phases in each framework vary, yet, a consensus is evident that RPA development projects consist of the following phases: selection and initialization (e.g., "process discovery", "task selection"), analysis and design (e.g., "process analysis", "procedure modifications", "assess bot"), implementation and testing (e.g., "development", "configure bot", "testing"), and operation and maintenance (e.g., "release", "run", "maintenance"). While the frameworks point towards SMEs being involved at least as citizen developers and potentially supported by a CoE, none provide specifications on how to involve and manage their roles and responsibilities.

3. Research Approach

Overall research strategy. Our study was motivated by the observation that even though RPA provides firms with a tool for easy and decentralized process automation, the associated responsibilities and role changes of SMEs, e.g., as analysts, citizen developers, and testers, complicate successful implementation. Thus, we aim to derive a software development framework that guides decentralized RPA development while supporting SMEs in their new roles and responsibilities. To this end, our study employs DSR to ensure practical relevance and scientific rigor (Hevner, 2007). We iteratively follow the three cycles of design DSR, i.e., the

Table 1. Overview of RPA development frameworks focusing on a decentralized approach.

Author(s)	Focus of the Framework	Development Phases	Specification of Roles and Responsibilities?
Flechsig et al. (2019)	Framework for combining RPA development with BPM on the project level	1) process identification, 2) process discovery, 3) process analysis, 4) process redesign, 5) development, 6) testing, 7) release, 8) run, 9) monitoring & control	No, but acknowledge SMEs as citizen developers
Herm et al. (2020)	Framework for initiating and scaling RPA projects on the organizational level	1) initialization, 2) implementation, 3) scaling	No, but acknowledge the supporting role of CoE
Huang and Vasarhelyi (2019)	Framework for developing RPA bots for auditing on the project level	1) procedure selection, 2) procedure modification, 3) implementation, 4) evaluation and operation	No, but acknowledge SMEs as citizen developers
Noppen et al. (2020)	Framework for initiating and scaling maintainable RPA projects on the organizational level	1) establish capability (vendor selection, creating a business case, developing a Proof of Concept), 2) develop capability (assess, configure, test bot), 3) mature capability (maintenance, scaling)	No, but acknowledge SMEs as citizen developers and the supporting role of CoE
Syed et al. (2020)	Guidelines for initiating and scaling RPA projects on the organizational level	1) pre-implementation, 2) RPA tasks selection, 3) stakeholders buy-in, 4) RPA roll-out, 5) development and management of bots, 6) long-term success	No, but acknowledge SMEs as citizen developers and the supporting role of CoE

relevance cycle to connect our study with real-world problems, the rigor cycle to incorporate the existing knowledge base, and the design cycle to develop and evaluate our framework (Hevner, 2007). We conducted two iterations of all three cycles. The first iteration focused on building an in-depth understanding of the challenges related to the roles and responsibilities of SMEs in decentralized RPA projects. The second iteration focused on deriving an RPA development framework addressing the identified challenges.

1st DSR iteration. We started with the relevance cycle by taking the case of decentralized RPA development at a large automotive corporation (more than 100,000 employees and revenue of over 99 billion USD as of 2020) with more than six years of RPA experience ("AutoCorp"). We conducted eight semi-structured expert interviews following the guidelines of Myers and Newman (2007) with SMEs involved in RPA projects and members of the firm's RPA CoE focusing on the challenges they experienced in decentralized RPA projects. The interviews lasted, on average, 46 minutes and resulted in over 360 minutes of taped and transcribed interviews. We then inductively analyzed the data (Yin, 2014) to understand challenges related to the roles and responsibilities of SMEs in decentralized RPA projects. Next, we ensured rigor by analyzing the literature on RPA for challenges in decentralized RPA projects. Finally, iterating between the practical and theoretical findings, we synthesized a list of challenges that complicate decentralized RPA projects resulting from the SMEs' local ownership and responsibilities for bot development as an interim artifact. We present the results of the first DSR iteration in Section 4.1.

2nd DSR iteration. We started with the rigor cycle by analyzing the literature on RPA for existing frameworks for decentralized RPA development. We assessed whether and how the frameworks addressed the challenges we had identified in the first iteration. On the one hand, we observed that none of the frameworks addresses the roles and responsibilities of SMEs in RPA projects. On the other hand, we found a lack of an overarching development framework for decentralized RPA projects. Nonetheless, four phases emerged as fundamental to the RPA development process (cf. Section 2.2). We then engaged in the relevance cycle by conducting semi-structured expert interviews (Myers & Newman, 2007) with six further SMEs involved in RPA projects and members of the firm's RPA CoE at AutoCorp. The interviews lasted, on average, 32 minutes and resulted in over 190 minutes of taped and transcribed data. We focused on discussing activities, best practices, and success factors that facilitate decentralized RPA development and address the identified challenges.

Finally, drawing on our insights from literature and practice, we entered the design cycle to iteratively design the RPA development framework as the final DSR artifact. To this end, we first identified from the literature activities relevant to the four phases of the RPA development lifecycle, such as process selection or implementation. Then, we analyzed which roles should be involved in each activity to ensure successful bot implementation and address the identified challenges of SMEs. Some roles emerged from literature, such as the RPA citizen developer or CoE (Noppen et al., 2020). Other roles emerged as best practices from our observations at AutoCorp, such as the RPA manager. Second, drawing on our practical insights, we identified additional important activities to support SMEs in decentralized RPA projects, such as assigning RPA roles and designing the bot and a schedule for implementation. Third, we derived success factors that further alleviate the identified challenges and contribute toward successful, decentralized RPA development. Finally, we evaluated the resulting framework in a focus group with six experts at AutoCorp and incorporated the obtained feedback. We present the resulting artifact in Section 4.2.

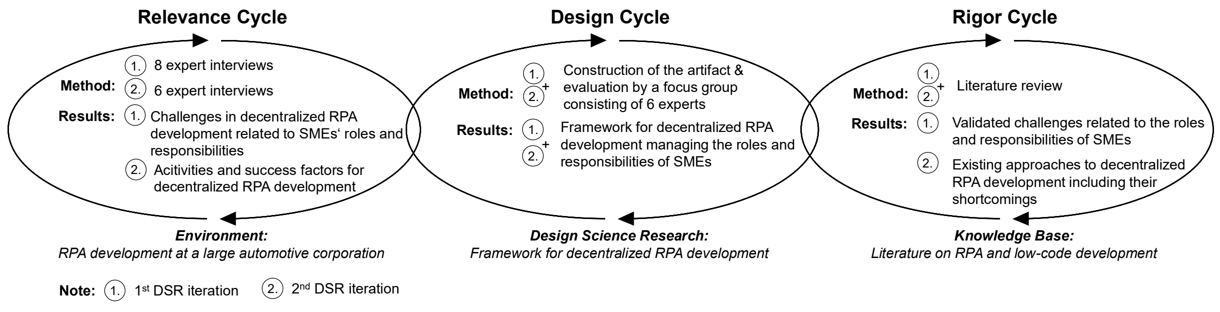

Figure 1. DSR research approach (own representation based on Löhe and Legner (2014) and Hevner (2007)).

4. Results

4.1 Challenges for SMEs in Decentralized RPA Development Projects

Informed by the first DSR iteration, we synthesized the challenges for decentralized RPA projects resulting from the SMEs' local ownership and development responsibilities (see Table 2). We illustrate the challenges according to the phases of the RPA development cycle (cf. Section 2.2). In addition, we present two overarching challenges.

Table 2. Overview of challenges.

Phase	ID	Challenge
Selection & Initialization	**CHAL-1**	Insufficient understanding of RPA capabilities and requirements
Analysis & Design	**CHAL-2**	Incomplete/ambiguous analysis and documentation of as-is processes
Implementation & Testing	**CHAL-3**	Lack of IT development knowledge and experience
Operation & Maintenance	**CHAL-4**	Maintenance responsibilities in the business unit
Overarching	**CHAL-5**	Balancing RPA developer and operational roles
	CHAL-6	Administrative overhead

The first challenge, related to the selection and initialization phase, is the SMEs' **insufficient understanding of the capabilities offered and the requirements posed by RPA**. Without an IT background, SMEs at AutoCorp reported "*not understanding the bigger picture*" (Expert H) and feeling insecure about how RPA works and which processes are suited for automation. These accounts resonate with literature that points towards the difficulties of SMEs to *"get [their] head[s] around what RPA actually is*" (Lacity & Willcocks, 2016b, p. 27) and to understand when it is best applied (Herm et al., 2020). In contrast, AutoCorp's CoE had accumulated experience with RPA technology, yet, they found they "*were not able to communicate to the business units what RPA is and how they can use it*" (Expert A).

The second challenge, which characterizes the analysis and design phase, consists of the **incomplete or ambiguous analysis and documentation of the as-is processes.** While SMEs usually have extensive knowledge of their work routines, this knowledge is considered tacit and, thus, difficult to express (Hallikainen et al., 2018). As a result, SMEs' process analysis and documentation, which also provide the basis for the bot implementation, might be superficial or incomplete (Cewe et al., 2018), e.g., lacking information on exceptions or workarounds. Even though screen-recording tools can alleviate the problem, they hardly capture every process variation, and thus, SMEs still have to articulate their process expertise (Syed et al., 2020). This problem is exacerbated if different SMEs document the process and implement the bot while both, albeit located in the same business unit, have "*their own, biased understanding of the process*" (Expert B). In addition, due to a lack of IT development experience, SMEs at AutoCorp reported that their process documentation often lacks "*technical details for the bot to function properly*" (Expert G), complicating the implementation.

The third challenge, in the implementation and testing phase, is due to SMEs being **untrained and inexperienced in IT development**. Even though RPA is considered a low-code automation solution that does not require programming skills (Lacity & Willcocks, 2015), the SMEs taking on the RPA citizen developer role at AutoCorp reported challenges. In particular, during training and their first implementations, they struggled with their limited experience and understanding of development basics, such as using programming patterns, for example, "*looping or nesting functions*" (Expert C), or structuring tasks in workflows for the bot to execute. Consequently, experts described "*feeling lost*" (Expert B) and unable to make fast progress, leading to demotivation and frustration for the SMEs. This challenge is exacerbated by the lack of a structured approach to guide SMEs through designing and developing bots. Instead, SMEs tend to start implementing without planning, resulting in complex, unstructured code. This observation is also mirrored by the dearth of research on designing and programming RPA bots (Ratia et al., 2018) and studies that describe the implementation as tedious and error-prone for SMEs (Syed et al., 2020).

The fourth challenge, in operation and maintenance, is the **business units' responsibility for maintaining bots**. Due to the local ownership, SMEs—and not the IT department—are accountable for monitoring the bot, fixing errors, and implementing changes over its lifetime, for example, when the underlying IT systems or processes change (Noppen et al., 2020). In addition, as the initial process analysis is often incomplete, bots malfunction and require adaption. Consequently, SMEs at AutoCorp reported spending over "*80% of [their] capacity on maintaining bots*" (Expert G), in particular for complex processes. Other experts even described bot maintenance as "*not possible without the technical support of the CoE [...] unless it is your full-time job, which it rarely is*" (Expert F). In addition, maintenance is complicated when responsibilities in the business unit shift, such as another SME taking over the developer role, but the process and implementation knowledge are undocumented. Maintaining the bot then requires the new developer to "*look into the code and try to figure out [him-/herself]: where do I start? [...] What is the process?"* (Expert D).

In addition, we identified two challenges that span the entire RPA cycle. The fifth challenge is experienced by SMEs as they have to **balance their RPA and operational roles** throughout the RPA development cycle. Because SMEs are usually not assigned as full-time RPA developers but instead take on RPA development on top of their operational duties, they find it difficult to structure their workdays consisting of these different tasks. The experts agreed they need time to get into an analytical mindset and familiarize themselves with the development tasks. Yet, that time might be sparse due to the commitments of their operational roles. Accordingly, "*the RPA [citizen] developer is always in multiple places at once and cannot fully concentrate on developing*" (Expert E). In addition, the SMEs described it as challenging to transition between their operational tasks, which often are routine, and the RPA-related tasks that they perceived to "*lack a clear structure and procedure*" (Expert H). This observation resonates with research pointing out RPA citizen developers' difficulties prioritizing their diverging roles and tasks (Osmundsen et al., 2019).

The **administrative effort** that accompanies RPA projects is the sixth challenge. Since the bot mimics employees' work in the firm's systems, it requires the same authorization and access rights as a human worker would need (Hofmann et al., 2020). Especially at a large corporation, such as AutoCorp, acquiring and managing these permits throughout the lifespan of a bot was reported to be time-consuming and distracting to the citizen developers, who only have limited time to invest in development. One developer described how "*the programming faded into the background, and I was more concerned with the administrative stuff: how do I get access to this system or to that drive?* " (Expert D).

4.2 Proposed Framework for Decentralized RPA Development

We present the RPA development framework that emerged from the second iteration of the DSR relevance and rigor cycles (see Figure 2). We derived a development framework that addresses the identified challenges of SMEs in decentralized RPA projects related to their roles and responsibilities. Our framework is based on an agile approach that encourages short and frequent iterations between its four phases. Research has shown that agile approaches enable firms to benefit from RPA (Syed et al., 2020). Before outlining the development phases with success factors in Section 4.2.2., we first present the roles that we identified as valuable for decentralized RPA projects.

4.2.1. Roles. First, we include **end-users**, who are the SMEs in a business unit using and working with the bot. Usually, these employees are knowledge workers, who are experts in the process, yet, lack an IT background (Lacity et al., 2016). Still, they need to document and hand over part of their process to the bot and subsequently work alongside it. Therefore, involving end-users throughout RPA development was reported to be a success factor at AutoCorp and is supported by research advocating for the business side to lead RPA development (Lacity et al., 2016). However, several end-users might work with one bot, so involving everyone is not feasible. Instead, representatives can be chosen to participate in development.

The second role is the **RPA manager** assigned to the RPA project. The RPA manager is located in the business unit and is responsible for managing the RPA project and providing administrative support until the bot is deployed. In particular, they are responsible for communicating with the end-users about requirements and project progress and coordinating with the IT department to acquire and manage infrastructure and system credentials needed for the bot. This role naturally emerged at AutoCorp over time to bundle the administrative overhead and relieve the RPA citizen developers of interfering bureaucratic tasks (cf. CHAL-6) and is similar to the role of the RPA program manager as reported by Lacity et al. (2016) in a case study at a large firm.

Third, the role of the **RPA citizen developer** is essential to developing and maintaining the bot. In decentralized RPA development, the RPA developer is an SME located in the business unit and, thus, usually lacks a background in IT. However, they might be knowledgeable about the process to be automated (Osmundsen et al., 2019). Therefore, the citizen developer requires sufficient technical training and support to fulfill their role. In addition, our interviews at AutoCorp showed that personal qualities, such as affinity for IT, open-mindedness for innovation and change, and the willingness to invest time and learn, make it easier to embrace their role.

Lastly, we include the role of an **RPA CoE** as research (Syed et al., 2020) and practice have shown that a CoE represents a valuable addition to the decentralized RPA development approach. The CoE can be located in the firm's IT department or comprise IT experts and is responsible for providing technical support, training, and overseeing all RPA projects. Yet, to reap the benefits of a decentralized approach, the CoE is not actively involved in developing, testing, and maintaining the bot as the ownership lies with the business unit (Osmundsen et al., 2019).

It is to be noted that depending on a firm's particular structure and size, the same employee can have multiple roles. For example, an SME might be the end-user, manager, and citizen developer of their bot.

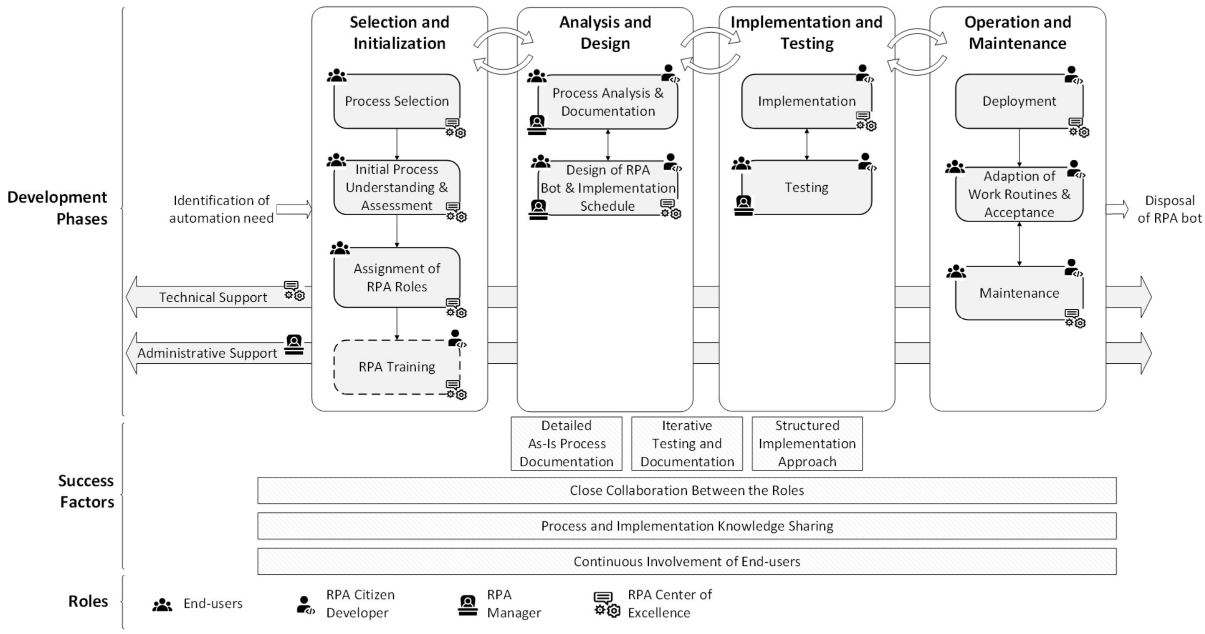

Figure 2. Proposed RPA development framework (own representation).

Nevertheless, the responsibilities of each role are relevant to efficient and successful development.

4.2.2. Phases. **Selection and Initialization.** This phase aims to select and assess a process for RPA automation and build the organizational foundations by assigning and training the required RPA roles. Business units initiate an RPA project upon discovering an **automation need** they expect to address with RPA. To this end, the SMEs who will later become the *end-users* **select the process (tasks)** to be automated. Since the SMEs in the business unit might lack sufficient understanding of RPA capabilities and requirements (cf. CHAL-1), the selection process is supported by the *CoE*, e.g., by providing information on exemplary cases of RPA automation or selection guidelines. To this end, research has yielded valuable insights into selection approaches, e.g., based on process mining (Wanner et al., 2019) or machine learning (Leopold et al., 2018).

As a result of these joint efforts, the *end-users* supported by the *CoE* **build a shared, initial understanding of the process and assess** its general suitability for automation with RPA. The success of this activity hinges on the CoE, as a party external to the process, to question the process and find out "*why are you [the SMEs] executing the process like that? Why do you need to automate it?*" (Expert I). All surfaced process knowledge should be documented as a basis for the following detailed process documentation.

If the automation proceeds, the *end-users* need to **assign the necessary RPA roles** within their business unit, i.e., the RPA citizen developer and RPA manager. As the end-users might be unsure of the roles and extent of their respective responsibilities, the *CoE* can guide the selection process. Additionally, to counteract the overwhelming workload that SMEs involved in RPA projects might experience (cf. CHAL-5), management should avoid placing all roles on one SME and restructure operational responsibilities to allow SMEs with RPA roles time for their new tasks.

Lastly, if necessary, the newly assigned RPA citizen developers receive **RPA training** provided by the RPA vendor and supported by the *CoE* with firm-specific best practices (cf. CHAL-3).

Analysis and Design. This phase is directed to analyzing and documenting the chosen process, designing the bot, and planning the implementation.

Detailed **process analysis and documentation** are success factors for implementing RPA bots. To this end, the business and technical representatives create the documentation in frequent iterations and adapt it during implementation and testing to preserve knowledge. On the one hand, several end-user representative*s* integrate their perspectives into a comprehensive picture of the process to avoid biased and incomplete documentation (cf. CHAL-2). In addition, the *RPA manager* points out inconsistencies and documents all surfacing information. On the other hand, to avoid a lack of technical foundation, the *RPA citizen developer* focuses on the technical feasibility of the documentation. If the developer is inexperienced, the *CoE* can support the technical assessment. Furthermore, process improvement or standardization options might emerge throughout the documentation, and the process is adapted accordingly. Finally, the process documentation should be detailed, e.g., by including screenshots of clicks in the system or screen recordings (Cewe et al., 2018).

Since citizen developers often perceive the implementation as complex and challenging (cf. CHAL-3), the developer planning the implementation technically and organizationally was reported as a success factor at AutoCorp. The *RPA citizen developer* thus **designs the bot and implementation schedule**. To this end, the citizen developer defines the bot functions, their interrelations, and the order and time of implementation, if needed, supported by the CoE (cf. CHAL-3). Meanwhile, ambiguities in the process documentation might emerge, which the citizen developer refers back to the *end-users* to clarify. Additional administrative requirements might surface (cf. CHAL-6), which the *RPA manager* attends to with the IT department. The resulting bot design prevents the developer from being distracted throughout the implementation and enables them to create structured code. In addition, the implementation schedule allows the citizen developers to allocate time for development and separate these timeslots from operational tasks to avoid overhead by frequent switching (cf. CHAL-5). Also, RPA citizen developers should allocate extra time to engage in research and training as needed.

Implementation and Testing. This phase aims at creating a bot deployable for productive use. Therefore, the *RPA citizen developer* **develops** the bot on an RPA low-code platform following the bot design. In addition, the *CoE* offers support, e.g., through walk-in sessions for RPA citizen developers to address problems.

The development process is iteratively integrated with **testing**, as indicated by previous research (Agostinelli et al., 2019; Cewe et al., 2018). This is particularly important as firms often lack a test environment for RPA; thus, bots are tested in the productive environment (Agostinelli et al., 2019). Therefore, the *citizen developer* is iteratively implementing and testing function by function, allowing for monitoring and early correction of errors. Besides, the *RPA manager* collects test cases and data from the *end-users* before and in parallel to the implementation. The citizen developer discusses any semantic errors during testing, such as missing process steps, with the *end-users*. As a result, process knowledge emerges that the *citizen developer* incorporates into the documentation to preserve knowledge for RPA maintenance (cf. CHAL-4), which was considered an important success factor for RPA projects at AutoCorp.

Operation and Maintenance. This phase is directed at deploying, using, and maintaining the bot. Once the bot passes all tests, it is **deployed** into the business unit's productive environment by the *citizen developer* supported by the *CoE*.

As the bot impacts the *end-users'* routines, they need to familiarize themselves with the bot and **adapt their behavior** to accommodate the virtual co-worker. Thus, the *RPA citizen developer* supports end-users in this process and answers questions on the bot's functionalities and requirements. New routines are defined in the business unit, and the *end-users* are granted time to explore these before providing **user acceptance** for the bot.

Once the bot is in use, **maintenance** is essential. As the bot, for example, relies on stable system interfaces, interface changes require changes in the bot's code. Usually, *end-users* observe such complications and work with the *RPA citizen developer* to solve the problem. Over time, new functional requirements for the bot might result in code changes. As these maintenance responsibilities are time-consuming (cf. CHAL-4), *RPA citizen developers* should be allowed to allocate time for maintenance tasks and receive support from the *CoE*. The cycle of operation and implementation continues until the bot is no longer needed and **disposed** of.

5. Discussion and Conclusion

Our study was motivated by the observation that decentralized RPA projects, even though promising to process automation, are complicated by the new roles and responsibilities SMEs need to meet. Thus, we synthesize these challenges and derive a software development framework that guides decentralized RPA projects while managing SMEs' different roles and responsibilities. Consequently, our research contributes to theory threefold.

First, we contribute to research on the organizational use of RPA by providing a structured overview of challenges related to SMEs' new roles and responsibilities in decentralized RPA projects. As RPA is an emerging technology, research thus far has mainly focused on studying the features of RPA platforms (Enríquez et al., 2020), practical applications scenarios (Lacity et al., 2016), and benefits (Asatiani & Penttinen, 2016) to understand when and why firms use the technology. In contrast, the process of developing bots has received less attention and has instead been addressed through lessons learned and experience reports (Syed et al., 2020). This might be due to how RPA is perceived as a low-code technology that SMEs outside of the IT department easily implement (Hofmann et al., 2020) and that, compared to other automation technologies such as BPM systems, does not require sophisticated implementation strategies (van der Aalst et al., 2018). However, our findings show that the process of decentralized RPA development is prone to challenges that firms need to be aware of and address to realize successful RPA projects. We identify six challenges that emerge as SMEs have to meet new roles and responsibilities related to IT development, such as citizen developers or IT project managers. Interestingly, these challenges differ from the challenges that firms learned to navigate for traditional IT projects, such as cost and time overruns or skilled labor shortage (Kumar, 2002). Thus, they call for new measures.

Second, our study contributes to the literature on RPA as a low-code technology (Bock & Frank, 2021) by reporting how the change of roles and responsibilities that SMEs experience in low-code RPA projects impacts the project's progress and success. While the literature on low-code development acknowledges that the decentralized development executed by citizen developers brings unique technical challenges (Hofmann et al., 2020) and can lead to the blurring and the reassignment of roles between the IT and business sides (Bygstad, 2017; Lacity & Willcocks, 2016a), these role changes and their consequences have not been studied thus far. Therefore, our study sheds light on the socio-technical side of low-code development by showing how the role transition of SMEs without IT background towards owning and executing low-code projects impacts the progress and outcome of development. While we studied the impact of such role changes in the context of RPA projects, future research might explore the transition process for different low-code technologies to assess how the identified challenges apply to further technological contexts and whether additional measures for supporting SMEs are required.

Third, we contribute to the literature on RPA by providing an overarching framework for decentralized RPA development that supports SMEs in their new roles and responsibilities. While research thus far primarily has addressed the initialization and scaling of RPA projects in firms (Herm et al., 2020; Syed et al., 2020), we still lack knowledge on the roles and responsibilities of SMEs in decentralized RPA projects and how to support them throughout the development process. To this end, our development framework specifies four RPA-related roles—end-users, RPA manager, RPA citizen developer, and CoE—and provides guidance on how these roles should engage during RPA development. As a result, we identify activities that firms should incorporate in the RPA development process in addition to established development activities to address the challenges of SMEs specifically, e.g., by assigning RPA roles and responsibilities, creating a schedule for RPA bot development, and iteratively adapting work routines and the bot to reach user acceptance. We also include success factors that firms should be aware of to ensure valuable decentralized RPA projects, such as process and implementation knowledge sharing and close collaboration between the roles involved. Overall, our framework, grounded in literature and practice, confirms the suitability of agile, iterative methods to guide RPA projects (Hofmann et al., 2020), but at the same time, stresses the importance of adapting traditional IT development methods to address the unique situation of SMEs in decentralized RPA development. As such, our framework, supporting SMEs in their new RPA-related roles and responsibilities, complements existing frameworks for decentralized RPA development that either focus on the introduction and scaling of RPA on the organizational level (Herm et al., 2020; Noppen et al., 2020; Syed et al., 2020) or the management of RPA on the project level for specific application scenarios (Flechsig et al., 2019; Huang & Vasarhelyi, 2019), yet, without providing specifications on how to support SMEs in their roles and responsibilities.

We acknowledge that our research is subject to several limitations. First, our practical insights are grounded on qualitative data from a large firm with hierarchical structures. Establishing and managing roles and responsibilities in RPA projects might unfold differently in small and medium-sized firms, where one employee might adopt several roles or resources for a company-wide CoE might be sparse. Although we corroborate these practical insights with theoretical findings from the DSR rigor cycle to ensure that the identified responsibilities and activities of RPA development apply across firm sizes and industries, studying the process of decentralized RPA development in small- and medium-sized firms could provide additional valuable insights. Second, even though our framework is grounded in literature and practice and was evaluated by a focus group at AutoCorp, it has not been applied to guide the execution of RPA projects in practice. Future studies, thus, could build upon our research to investigate the usage of the framework in practice and derive lessons learned from its practical application. Overall, our study provides a first step toward acknowledging and managing the challenges of decentralized RPA projects.

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Appendix B.5 P5: Assessing Process Mining Use Cases: A Taxonomy of Antecedents and Value Potentials of Process Mining

Assessing Process Mining Use Cases: A Taxonomy of Antecedents and Value Potentials of Process Mining

Completed Research Full Paper

Julia Eggers
Technical University of Munich, Germany
julia.eggers@tum.de

Marie-Christin Häge
University of Mannheim, Germany
marie-christin.haege@soft-consult.net

Sina Zimmermann
Neu-Ulm University of Applied Sciences and Technical University of Munich, Germany
sina.zimmermann@hnu.de

Heiko Gewald
Neu-Ulm University of Applied Sciences, Germany
heiko.gewald@hnu.de

Abstract

Process mining (PM) has gained traction as a Big Data Analytics technique to discover, monitor, and improve business processes based on event data that are available in organizations' information systems. However, despite high expectations and widespread use in practice, organizations still struggle to implement and realize value from PM. In particular, organizations, first, are challenged to identify and establish the antecedents necessary for implementing PM use cases, and second, lack guidance in identifying and assessing valuable PM use cases. Even though initial studies investigated sociotechnical factors influencing the adoption, implementation, and value of PM on the organizational level, knowledge in the field is still fragmented, and we lack a systematic understanding of how organizations can assess antecedents for and value potentials of PM to identify valuable use cases. Thus, building on a design science research approach, we address this research gap by developing and evaluating a structured framework drawing on the taxonomy development method of Nickerson et al. (2013) for assessing PM use cases based on their antecedents and expected value potentials. We iteratively develop and evaluate the taxonomy grounded in theory by drawing on PM literature and related research fields and practice by conducting twelve semi-structured interviews at a German manufacturing corporation to apply and evaluate the taxonomy. Consequently, our study contributes to research on the organizational implementation and use of PM and enables researchers and practitioners to understand, operationalize, and assess the factors influencing the selection of PM use cases.

Keywords

Process mining, taxonomy, framework, design science, cost-benefit assessment.

Introduction

Over the last decade, organizations have adopted big data analytics (BDA) to leverage their abundance of data for improved products, strategies, and processes (van der Aalst, 2016). Against this backdrop, in particular, process mining (PM) has gained traction in recent years as a BDA technique to discover, monitor, and improve business processes based on event data that are available in organizations' information systems (IS) (Badakhshan et al., 2022). Hence, PM allows organizations to create unprecedented and continuous transparency of their end-to-end business processes as the foundation for process improvements (Grisold et al., 2020). As organizations increasingly adopt PM, its market volume has increased and is expected to reach $2.3 billion by 2025, with an annual growth rate of 33% (Biscotti et al., 2021). This trend is underlined by a recent survey of 106 organizations that showed a 63% adoption rate of PM, with 87% of non-adopters planning on or implementing pilot projects (Galic & Wolf, 2021).

However, despite high expectations and widespread use in practice, organizations still struggle to implement and realize value from PM. For example, organizations fail to implement PM due to technical factors, such as availability and quality of event data, but also due to organizational factors, such as a lack of guidance on required process properties for successful PM implementation (Grisold et al., 2020). In addition, surveys show that only 9% of the organizations using PM achieved the desired improvement for their use case (Galic & Wolf, 2021). These observations indicate that organizations, first, struggle to identify and establish the antecedents necessary for implementing PM use cases, and second, lack guidance in assessing and realizing value from PM use cases. Still, organizations need to overcome these challenges not only to adopt but, in particular, to continuously identify and implement successful PM use cases where the expected benefits outweigh the required implementation effort (Grisold et al., 2020).

However, we do not know how organizations can identify valuable PM use cases (Martin et al., 2021), as PM research has mainly focused on advancing the technical foundation (Thiede et al., 2018). Only recently has research shifted toward sociotechnical questions of PM use (Badakhshan et al., 2022). For example, studies have yielded insights into factors influencing PM adoption (Rott & Böhm, 2022), organizational success factors for PM use (Eggers & Hein, 2020; Mans et al., 2013), and the affordances provided by PM, such as visualization of end-to-end processes, that organizations leverage to achieve business values (Badakhshan et al., 2022). While these studies provide a valuable starting point by shedding light on the sociotechnical factors influencing the adoption and benefits of PM on the organizational level, knowledge in the field is fragmented, and we lack a systematic understanding of how organizations can assess antecedents for and value potentials of PM to identify valuable use cases (Eggers & Hein, 2020; Grisold et al., 2020; Martin et al., 2021). Thus, we set out to address the following research question: *How can organizations assess the antecedents and expected value potentials of PM use cases?*

Following a design science research (DSR) approach (Hevner et al., 2004) and the taxonomy development method of Nickerson et al. (2013), we address this research question by developing and evaluating a structured framework for assessing PM use cases based on antecedents and value potentials. Thus, our study contributes to research on PM implementation and use and provides insights for researchers and practitioners to understand, operationalize, and assess factors influencing PM use case selection.

Related Work

Process Mining

While PM only emerged in the mid-90s, its technical basis has since advanced, leading to commercially available PM tools used by organizations "*to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today's systems*" (van der Aalst, 2016, p. 31). Conducting PM requires organizations to create event logs by leveraging sequentially recorded event data that reflect the traces of a process in the underlying IS (van der Aalst, 2016). As such, PM does not provide a (subjective) snapshot of the process landscape but creates continuous transparency of everyday activities as they are carried out in the firm (Badakhshan et al., 2022). By analyzing event logs with PM, organizations can (1) *discover* process models without prior knowledge to create transparency, (2) check their processes for *conformance* with an a priori-defined process model, thus, allowing them to notice deviations between actual and desired processes, and (3) *enhance* existing process models to reflect characteristics of the actual process (van der Aalst et al., 2012).

While research on PM initially has focused on technical questions, such as improving algorithms and event logs (Thiede et al., 2018), recently, scholars increasingly focus on the organizational use of PM (Badakhshan et al., 2022). In particular, studies show that organizations across industries now use PM, ranging from healthcare over manufacturing to public administration (Thiede et al., 2018), for a variety of processes, ranging from department-specific sub-processes to organization-wide end-to-end processes (Eggers et al., 2021). In addition, studies report on PM implementation for specific use cases, that is, applying PM to a process with specific goals, such as uncovering fraud in auditing (Jans et al., 2014).

Assessing Process Mining Use Cases

PM can be applied to any process providing event data (van der Aalst, 2016), which challenges organizations to identify and assess PM use cases that will prove valuable in light of the implementation effort and expected value. For example, using PM to detect fraud in a standardized purchase-to-pay (P2P) process in an ERP system (Jans et al., 2014) may require less effort than analyzing waste in customized production processes (Knoll et al., 2019). Thus, assessing the cost-benefit ratio of PM use cases is crucial (Grisold et al., 2020). This assessment facilitates the initial adoption of PM by identifying feasible initial use cases to create a positive experience (Rott & Böhm, 2022) and supports organizations in defining a mid- or long-term strategy for PM application to ensure continuous use and value realization (Grisold et al., 2020). Additionally, research shows that PM use cases in organizations change over time, for example, from initially analyzing local sub-processes to complex end-to-end processes (Eggers et al., 2021).

To this end, organizations need to evaluate whether the value potentials for a PM use case outweigh its required implementation effort. On the one hand, organizations strive for *value potentials* through PM that yield opportunities for realizing monetary values, such as optimizing working capital, and non-monetary values, such as increased compliance (Badakhshan et al., 2022; Martin et al., 2021). The value potentials depend on the use case and PM application. For example, organizations can use PM to create process transparency to identify bottlenecks (vom Brocke et al., 2021), understand process compliance (Martin et al., 2021) or analyze process performance (Knoll et al., 2019). On the other hand, organizations must invest the *effort to establish the antecedents* for PM on the technical and organizational levels (Eggers & Hein, 2020). Organizations need to ensure technical readiness, such as accessing event data of the right quality (van der Aalst et al., 2012). In addition, organizational antecedents influence PM success, such as management support and PM expertise in the workforce (Mans et al., 2013). Depending on the use case, antecedents may manifest in varying degrees. Hence, the *operationalization* of antecedents and value potentials to measure their manifestation is crucial to use case assessment.

In sum, to assess PM use cases, organizations require a systematic understanding and operationalization of necessary antecedents and expected value potentials to decide for or against a PM use case. However, our knowledge of antecedents and value potentials is fragmented and lacks systematic and usable guidance on how to assess PM use cases. A notable exception provides the study of Rott and Böhm (2022) that derives a method for organizations to decide on PM adoption based on the selection of an initial use case. Yet, we still lack knowledge of how to systematically determine the effort for and value of PM use cases for continuous use and value realization (Grisold et al., 2020).

Method

We draw on the taxonomy development method of Nickerson et al. (2013) to develop a systematic and usable framework for assessing PM use cases based on antecedents and expected value potentials. In particular, a taxonomy allows the organization of knowledge in a field, such as extant knowledge on PM antecedents and value potentials, and the identification of relationships among the underlying concepts, such as assessing the cost-benefit ratio for PM use cases (Nickerson et al., 2013). To ensure a scientifically rigorous and practically relevant approach, the taxonomy development method is embedded into the three cycles of DSR (Hevner et al., 2004). Thus, the development approach iteratively builds on the rigor cycle to ground the taxonomy in extant research, the relevance cycle to connect the taxonomy to the real-world application domain, and the design cycle to iteratively refine the taxonomy by processing input from the previous two cycles (Hevner et al., 2004; Nickerson et al., 2013). Our taxonomy development unfolded in iterations of the empirical-to-conceptual approach, that is a design cycle informed by empirical data from the relevance cycle, and the conceptual-to-empirical approach, that is a design cycle informed by extant research from the rigor cycle, until predefined ending conditions are met (Nickerson et al., 2013). This procedure allowed us to base our taxonomy on extant research while iteratively enriching it with insights from practice and validating these insights with literature. In total, we developed our taxonomy for PM use case assessment based on four design iterations, as illustrated in Figure 1.

In the first step, we determined the **meta-characteristics** of the taxonomy, which are correlated with the taxonomy's purpose (Nickerson et al., 2013). In our case, the taxonomy's purpose is to *systematically classify the antecedents and value potentials of PM to enable the assessment of PM use cases*. Additionally, we adopted the eight objective and five subjective **conditions for ending** the iterative development as proposed by Nickerson et al. (2013). In particular, the development terminates when all representative PM cases identified can be classified with the taxonomy; no case was merged or split in the last iteration; at least one case relates to every characteristic; no new dimensions or characteristics were added, merged or split in the last iteration; every dimension is unique; every characteristic is unique within its dimension, and each combination of characteristics is unique (objective), and the taxonomy is concise, robust, comprehensive, extendible, and explanatory (subjective) (Nickerson et al., 2013).

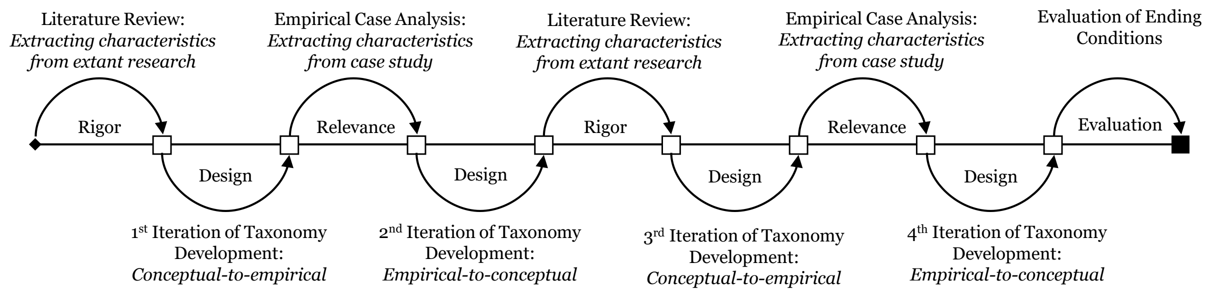

Figure 1. Iterative development of the taxonomy embedded in the DSR approach.

Then, we started the **first iteration** of taxonomy development based on the conceptual-to-empirical approach to build the foundation for our taxonomy from extant research. We thus employed a rigor cycle with a structured literature review (SLR) (Webster & Watson, 2002). To this end, we defined the search string (i.e., "process mining" AND ("value" OR "success" OR "taxonomy")) and searched the Association for Information Systems e-Library, Web of Science, and the Institute of Electrical and Electronics Engineers Xplore Library to account for findings in the most relevant journals and conferences in the IS field, and findings from computer science, where the topic of PM first emerged. The search resulted in 9,813 articles, of which we removed duplicates and non-German/-English publications. Then, analyzing title, abstract, and keywords, we selected studies that systematically focus their research endeavor on (1) the organizational management and use or (2) antecedents/success factors or (3) value potentials of PM (and not only address these topics peripherally, for example, in the context of technical development). Finally, we narrowed the set down to 38 papers after forward and backward search (Webster & Watson, 2002). Analyzing the articles, we identified an initial set of dimensions as antecedents for PM, that is, *Resource Availability, Management Support, Process Miner Expertise, Data & Event Log Quality* (Mans et al., 2013)*, Stakeholder Commitment, Process Model Awareness*, *Process Mining Type* (Fischer et al., 2019), *Amount of Raw Data*, *Availability of Raw Data,* and *Number of IS* (Hawking & Sellitto, 2010; van der Aalst et al., 2012). In addition, we identified *Process Complexity* and *Business Relevance* (Mans et al., 2013; Rott & Böhm, 2022) as dimensions relating to value potentials. Next, we defined characteristics for each dimension drawing on the PM literature or complementing it with related literature, such as BPM and IT-enabled change. As the ending conditions were not yet met, we initiated the next iteration.

In the **second iteration**, we followed an empirical-to-conceptual approach to improve our taxonomy's practical consistency by collecting qualitative data at "Alpha," a German manufacturing firm with 9,500 employees (2019) striving to expand their PM application. We conducted six semi-structured interviews with process and IS experts (Myers & Newman, 2007) that lasted 30 to 60 minutes and were analyzed through qualitative data analysis (Gläser & Laudel, 2009). The interviews focused on evaluating the taxonomy by applying it to two use cases, order-to-delivery (O2D) and P2P. Based on the interviews, we split the dimension *Business Relevance* into *Business Volume* and *Business Criticality* and the dimension *Stakeholder Commitment* into *Process Owner Commitment* and *End User Commitment* to reflect a more nuanced understanding and added the dimension *Size* to reflect the process scope. Additionally, the interviewees highlighted that the antecedents and value potentials of PM should be distinct in the framework. Thus, we needed to reiterate the literature to clarify this distinction.

Therefore, the **third iteration** followed the conceptual-to-empirical approach engaging with the PM literature. We divided the taxonomy into two parts reflecting the antecedents for and value potentials through PM. In addition, we integrated the dimension *PM Type*, as it was only focused on the technical use of PM, into the new dimension *Potential,* which summarizes PM value potentials, (*Transparency, Conformance Checking, Process Monitoring, Performance Analysis, Forecasting* (Badakhshan et al., 2022; Martin et al., 2021)). As a result of the changes, an additional taxonomy iteration was necessary.

Thus, the **fourth iteration** followed an empirical-to-conceptual approach to evaluate the modified taxonomy practically. Therefore, we conducted six additional interviews to identify two further use cases at Alpha, the return and the offer processes, and to evaluate the taxonomy by applying it to the use cases. No more changes resulted from the application. In addition, all dimensions and characteristics within each dimension were unique, and the taxonomy fulfilled the ending conditions as it was concise, robust, comprehensive, extendible, and explanatory (Nickerson et al., 2013). Consequently, we concluded the taxonomy development. To ensure the final taxonomy is applicable and useful, we included an additional evaluation (Kundisch et al., 2021) by applying it to the two use cases we identified in the second iteration.

Results

Taxonomy for the Assessment of Process Mining Use Cases

Table 1 presents the final version of our taxonomy. The taxonomy is visualized through two morphological boxes containing 20 dimensions that describe the antecedents for and value potentials of PM for any use case. Each dimension consists of three to five mutually exclusive characteristics that indicate how each dimension can manifest for the given use case. These manifestations are then averaged to gauge and contrast the expected magnitude of value potentials and effort for applying PM. The value and effort are indicated on an ordinal scale from S to XXL, similar to t-shirt sizes, which is a common approach for effort estimation in software development since it is relatable to practitioners (Alostad et al., 2017).

Meta-Dimensions	Dimensions	Characteristics				
Business Relevance	Business Volume	low	medium	high		
	Business Criticality	minor	important	vital	mission-critical	
Potential	Transparency	low potential	medium potential	high potential		
	Conformance Checking	low potential	medium potential	high potential		
	Process Monitoring	low potential	medium potential	high potential		
	Performance Analysis	low potential	medium potential	high potential		
	Forecasting	low potential	medium potential	high potential		
Value Potential		**S**	**M**	**L**	**XL**	**XXL**

Meta-Dimensions	Dimensions	Characteristics				
Organizational/ Project Specific	Resource Availability	no	low	medium	high	
	Management Support	indifferent	observing	supporting	involved	
	Process Owner Commitment	will block to make it happen	none	let it happen	help it happen	make it happen
	End User Commitment	will block to make it happen	none	let it happen	help it happen	make it happen
Process Mining Related	Process Miner Expertise	Novice	Advanced Beginner	Competent	Proficient	Expert
	Process Awareness	none	referential	partial	complete	
Process Specifc	Size	large	moderate	small		
	Complexity	high	medium	low		
IS and Data Related	Quality of Raw Data	low	medium	high		
	Amount of Raw Data	small	moderate	large		
	Availability of Raw Data	no	partial	complete		
	Quality of Event Log	poor	fair	good	very good	excellent
	Number of IS	more than 4	4	3	2	1
Effort for Establishing Antecedents		**XXL**	**XL**	**L**	**M**	**S**

Table 1. Taxonomy of PM antecedents and value potentials for use case assessment.

The first section of the taxonomy, **Value Potential**, consists of two meta-dimensions, Business Relevance and Potential. The meta-dimension 'Business Relevance' reflects the importance of the process to the organization. Thus, the first dimension ***Business Volume*** describes the financial volume associated with the use case, for example, the financial volume generated or processed, and thus, also the potential financial impact of process improvements (Bandara et al., 2005; Mans et al., 2013). Consequently, the business volume is characterized as *low, medium,* and *high*. Second, the dimension ***Business Criticality*** is defined as the necessity of the process for the business, which is reflected in the implications if the process is disrupted (Bandara et al., 2005; Mans et al., 2013). Business critical processes are identified through risk management and can be classified as *minor, important, vital,* and *mission-critical* (Snedaker, 2014).

The second meta-dimension, 'Potential,' reflects the value potentials of PM use for the use case. Therefore, it comprises five dimensions: ***Transparency, Conformance Checking, Process Monitoring, Performance Analysis,*** and ***Forecasting*** (Badakhshan et al., 2022; Eggers & Hein, 2020; Martin et al., 2021). Each dimension describes a value potential depending on PM use, stakeholders' interests, their current knowledge of the process, and previous PM application (vom Brocke et al., 2021). For example, interviewees expressed that while process bottlenecks are transparent, they lack a tool to detect process fraud. The dimensions are characterized as *low potential, medium potential,* and *high potential*.

The second section of the taxonomy, **Effort for Establishing Antecedents,** consists of four meta-dimensions reflecting PM antecedents, i.e., Organizational/Project Specific, PM Related, Process Specific, and IS and Data Related. The meta-dimension 'Organizational/Project Specific' focuses on organizational antecedents. Thus, the first dimension, ***Resource Availability,*** describes the "*degree of information available from the project stakeholders during the entire process mining analysis*" (Mans et al., 2013, p. 13) and is based on employees' availability, time, and skill set related to the use case (Grisold et al., 2020). Literature characterizes this dimension as *no, low, medium,* or *high* (Smit & Mens, 2019). Second, the dimension ***Management Support*** reflects the senior management's willingness and commitment to the PM use case, for example, by devoting resources to the PM project (Hawking & Sellitto, 2010), which is characterized as *indifferent, observing, supporting,* and *involved* (Mans et al., 2013). Last, the dimensions ***Process Owner Commitment*** and ***End User Commitment*** describe the willingness and participation of process owners and employees executing the process to use PM for their use case and leverage its results (Fischer et al., 2019). Both dimensions are characterized by the attributes *will block to make it happen, none, let it happen, help it happen,* or *make it happen* (Benjamin & Levinson, 1993).

The meta-dimension 'PM Related' focuses on antecedents for using PM. First, the dimension ***Process Miner Expertise*** describes employees' skill set, experience, and expertise in preparing and conducting PM (Mans et al., 2013), which is characterized as *Novice, Advanced Beginner, Competent, Proficient,* and *Expert* (Bobay et al., 2009). The second dimension, ***Process Awareness***, reflects how well the project team members understand the process, know who and what systems are involved, and can explain the process model with its variations (Fischer et al., 2019). Research indicates that process awareness can be characterized as *none, referential, partial,* and *complete* (Sillaber & Breu, 2015).

Next, the meta-dimension, 'Process Specific,' consists of antecedents that characterize the use case and, thus, influence the level of difficulty in conducting PM (Mans et al., 2013). The first dimension **Size** defines the number of process activities on its highest granularity level, which we characterize as *large, moderate,* and *small* for a given use case. Second, ***Complexity*** focuses on process variability and standardization, thus indicating the difficulty when analyzing, understanding, and explaining a process (Cardoso, 2005). Complexity can be characterized as *low, medium,* and *high* (Smit & Mens, 2019).

The final meta-dimension, 'IS and Data Related,' covers technical antecedents for using PM. The first dimension, ***Quality of Raw Data***, defines the extent to which process raw data can be used for creating an event log PM (van der Aalst et al., 2012), operationalized as *low, medium,* or *high* usability of the data (Smit & Mens, 2019). Furthermore, the dimension ***Amount of Raw Data*** reflects the quantity of raw data, which is important since a larger data set correlates with higher confidence scores of the PM results (Grisold et al., 2020). As the amount of raw data relates to the frequency of the process (Grisold et al., 2020), this dimension is approximated by characterizing the process runs per year as *small, moderate,* or *large*. In addition, the raw data need to be accessible in the required form reflected in the dimension ***Availability of Raw Data***. The availability describes the fraction of data available for the use case as *no, partial,* and *complete* (van der Aalst et al., 2012). Once the data is available and preprocessed, the resulting ***Quality of the Event Log***, in particular in terms of completeness, trustworthiness, semantics, and safeness, influences the success of the PM use case. Thus, literature characterizes event log quality as *poor, fair, good, very good,* and *excellent* (van der Aalst et al., 2012). Last, the dimension ***Number of IS*** gives an indication of how many IS are used in the selected use case, characterized as *more than 4, 4, 3, 2,* and *1,* which influences the accessibility of the raw data and quality of the event log. The more IS are involved, the higher the effort and the level of difficulty in extracting the data (Hawking & Sellitto, 2010).

Evaluation of the Taxonomy at Alpha

We evaluated the final taxonomy by presenting it to the interviewees and applying it to assess four PM use cases we identified at Alpha. For the sake of brevity, we only present the assessment of the O2D process to illustrate the taxonomy's practical usability (see Table 2). Alpha had identified the O2D process as a PM use case because of delivery delays due to unclear reasons. Alpha's O2D process unfolds between the production plants and the subsidiaries, starting with an order from the subsidiaries reaching the production plant and terminating with the products arriving at the subsidiary.

Meta-Dimensions	Dimensions	Characteristics				
Business Relevance	Business Volume	low	medium	high		
	Business Criticality	minor	important	vital	mission-critical	
Potential	Transparency	low potential	medium potential	high potential		
	Conformance Checking	low potential	medium potential	high potential		
	Process Monitoring	low potential	medium potential	high potential		
	Performance Analysis	low potential	medium potential	high potential		
	Forecasting	low potential	medium potential	high potential		
Value Potential		**S**	**M**	**L**	**XL**	**XXL**

Meta-Dimensions	Dimensions	Characteristics				
Organizational/ Project Specific	Resource Availability	no	low	medium	high	
	Management Support	indifferent	observing	supporting	involved	
	Process Owner Commitment	will block to make it happen	none	let it happen	help it happen	make it happen
	End User Commitment	will block to make it happen	none	let it happen	help it happen	make it happen
Process Mining Related	Process Miner Expertise	Novice	Advanced Beginner	Competent	Proficient	Expert
	Process Awareness	none	referential	partial	complete	
Process Specifc	Size	large	moderate	small		
	Complexity	high	medium	low		
IS and Data Related	Quality of Raw Data	low	medium	high		
	Amount of Raw Data	small	moderate	large		
	Availability of Raw Data	no	partial	complete		
	Quality of Event Log	poor	fair	good	very good	excellent
	Number of IS	more than 4	4	3	2	1
Effort for Establishing Antecedents		**XXL**	**XL**	**L**	**M**	**S**

Table 2. Application of the final taxonomy to assess Alpha's O2D use case.

The interviewees first assessed the expected *value potential* of applying PM to the O2D process. To this end, the interviewees classified the ***Business Volume*** and ***Business Criticality*** as *high* and *mission-critical* since the process is essential to Alpha's operations as subsidiaries rely on receiving the ordered products, which are continuously produced and shipped to the subsidiaries. The interviewees expected a *high potential* for ***Transparency*** through PM on the O2D process. In addition, they anticipated a *high potential* of PM for ***Performance Analysis*** since the O2D process relies on the fast delivery of products to the subsidiaries to ensure customer satisfaction. PM use for ***Conformance Checking***, ***Process Monitoring,*** and ***Forecasting*** was of interest to the interviewees but only in the mid- or long-term after realizing initial values from transparency and performance analysis, resulting in *medium potential*. After averaging all dimensions, the resulting *Improvement Potential* was classified as *XL*.

Second, the interviewees used the taxonomy to *estimate the expected effort for establishing PM antecedents* for the O2D use case. First, the interviews revealed that the department had already discussed the resources necessary to implement PM for the use case, and they were dedicated to providing them in the long term. As such, the ***Resource Availability*** was characterized *high*. In addition, Alpha's ***Management Support*** was described as *involved* in the PM initiative since the management team had already supported the implementation of a PM proof-of-concept and strived to expand PM application at the firm. Similarly, the O2D ***process owner showed commitment*** to the PM use case as he recognized the potential of PM and wanted to *make it happen* to improve his process. Nevertheless, from his perspective, some of the employees involved in the process were hesitant toward PM due to time constraints and lack of experience, even though positivity and openness prevailed overall. Consequently, the ***End User Commitment*** was classified as *help it happen*. As no PM projects have been conducted in the department, the ***Process Miner Expertise*** was considered *Novice*. The ***Process Awareness*** was classified as *complete* since the interviewees described the process as well-known to the workforce and relatively compliant with the predefined standard process. The process-specific antecedents, ***Size*** and ***Complexity***, were characterized as *moderate* and *medium*. The process consists of several activities, which are known and manageable, such that the interviewees considered the process standardized. Nevertheless, the interviewees expected PM to reveal unknown process variants. In terms of IS and data-related antecedents, the interviewees stressed that a *large* ***Amount of Raw Data*** is available since the process is executed daily in the firm's ERP and transport management systems. Thus, only *two* ***IS are***

involved in process execution. Since Alpha relies on SAP as their ERP system, which is a frequent source system for PM, the ***Event Log Quality*** was characterized as *very good*. Still, the ***Quality of the Raw Data*** was assessed as *medium* since the interviewees described inconsistencies in the data that they also hoped to improve through PM. Lastly, the interviewees defined the ***Availability of Raw Data*** as *partial* since parts of the process are executed unrecorded via e-mail or phone. However, as this relates only to a fraction of the process, they still considered the data a usable foundation for PM.

In conclusion, for Alpha's O2D process, the *Improvement Potential* resulted in a rating of *XL* after averaging the dimensions, thus outweighing the *Effort Estimation,* which averaged at a rating of *M*. Thus, the outcome leads to the conclusion that Alpha's O2D process is a valuable use case for PM.

Discussion and Limitations

Our study was motivated by the observation that organizations strive to use PM to improve their processes but still lack guidance on identifying valuable PM use cases throughout the PM lifecycle. To this end, we synthesized and operationalized the fragmented literature on antecedents for and value potentials of PM and developed and evaluated a taxonomy for PM use case assessment. In the following, we discuss how our study contributes to research and practice and outline its limitations.

First, we contribute to the literature on the organizational implementation of PM (Badakhshan et al., 2022) by providing a structured overview of the antecedents and value potentials of PM. While prior studies on PM yielded insights into success factors (Mans et al., 2013) and benefits (Martin et al., 2021), and lessons learned from specific implementations (Reinkemeyer, 2020), the research is fragmented and lacks a systematic and applicable overview. Thus, we synthesize and classify the knowledge about what firms need to provide for and can expect from applying PM to specific use cases. The resulting taxonomy incorporates factors that are frequently referred to as essential for successful PM use cases, such as data quality, availability, and quantity (van der Aalst et al., 2012), but also draws attention to factors rarely considered in previous studies, such as process owner and end user commitment and process awareness. Yet, our application of the taxonomy at Alpha showed that these factors are equally important when assessing PM use cases. For example, when assessing Alpha's offer process based on the taxonomy, the interviewees indicated a good data basis for PM but expressed reluctance in the department's workforce to use PM due to time constraints and limited process awareness, which would require higher effort to interpret PM results. As a result, our taxonomy highlights that even though PM is a versatile BDA technology that can be used for most processes in organizations (van der Aalst, 2016), the selection of use cases is a nuanced procedure that requires organizations to consider multiple sociotechnical factors.

Second, our study sheds light on the operationalization of cost-benefit assessments for PM use cases (Grisold et al., 2020) by defining systematic characteristics for assessing the effort and value related to implementing PM use cases. Thus far, research has yielded case studies on factors leading to the implementation of specific PM use cases (Reinkemeyer, 2020) but provided limited insights into the operationalization of these factors. As a result, the cost-benefit assessment for PM use cases remains a challenge to firms, and its operationalization is unaddressed in PM research (Grisold et al., 2020). Hence, our taxonomy provides the first systematic operationalization of factors influencing the decision for a PM use case by offering characteristics synthesized from the PM literature and related research and evaluated in practice. We describe the characteristics in detail to enable a common understanding for stakeholders when assessing a use case and show their application in practice at Alpha where the taxonomy proved to be a valuable tool to gauge the expected effort and value for a PM use case. Consequently, our taxonomy enables scholars and practitioners to perform a structured assessment of PM use cases.

Third, our taxonomy contributes to research on the strategic use of PM (Badakhshan et al., 2022) by supporting organizations in defining a mid- or long-term strategy for PM application (Grisold et al., 2020). While research indicates that the use of PM in organizations changes over time, for example, from analyzing standardized sub-processes to analyzing complex end-to-end processes (Eggers et al., 2021), we know little about how organizations can define use cases for different times in the PM lifecycle (Grisold et al., 2020). To this end, our taxonomy supports organizations in assessing and prioritizing use cases for short-, mid-, or long-term implementation. For example, the assessment of four use cases at Alpha led the interviewees to the conclusion to implement the P2P process use case in the short term due to high expected value and low effort but implement the—although promising—return process use case in the mid-term due to high expected implementation effort that could benefit from more PM experience. In addition, based on the systematic characteristics underlying every dimension, our taxonomy provides the flexibility to reflect changes in antecedents and value potentials over time, for example, as PM expertise in a department improves or data quality deteriorates, such that use cases can be re-evaluated at any time.

Consequently, our study offers practitioners a deepened and systematic understanding of antecedents for and value potentials of PM and provides them with a usable tool to assess potential PM use cases. In particular, our taxonomy points practitioners toward what factors to consider when planning to implement a PM use case and how to measure them. Additionally, these insights can be leveraged to anticipate challenges during implementation, such as lack of data or skills in the workforce, and define necessary preparatory activities to address these challenges before they arise. Last, practitioners can use the assessments based on the taxonomy to argue for (or, if the better choice, against) potential PM use cases based on a transparent and objective foundation.

We acknowledge that our study is subject to several limitations that open up avenues for future research. First, even though we grounded our taxonomy in the literature on PM and related research through an SLR, the literature on the organizational use of PM emerged only recently. Thus, additional factors relevant to PM use case assessment might be accessible by collecting empirical data in the field. We, therefore, encourage scholars to conduct case studies on the organizational use of PM with a particular focus on what factors influence the decision for a use case. Second, we evaluated our taxonomy by applying it to four use cases at Alpha which demonstrated the taxonomy's applicability and practitioners' intention to use it, but, as the scope of this study was focused on the PM use case assessment phase, we could not cover the implementation phase of the selected use cases. However, we think that future research taking a longitudinal perspective by using the taxonomy to select use cases and evaluate the use cases after implementation could yield further valuable insights into its practical performance.

Conclusion

Organizations nowadays can generate unprecedented transparency on almost all of their processes with PM (van der Aalst, 2016), yet this comes with the inherent challenge of choosing use cases for PM application. Addressing this challenge, our study synthesizes and operationalizes the fragmented literature on antecedents for and value potentials of PM and, building on this theoretical foundation, develops a taxonomy for PM use case assessment which we evaluate by assessing four PM use cases at a German manufacturing organization. We hope that our taxonomy serves as a starting point for researchers and practitioners alike to reflect on the effort and potential related to PM and to support the systematic selection of PM use cases throughout the PM lifecycle.

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Appendix B.6 P6: Leveraging Big Data for M&A: Towards Designing Process Mining Analyses for Process Assessment in IT Due Diligence

Leveraging Big Data for M&A: Towards Designing Process Mining Analyses for Process Assessment in IT Due Diligence

Completed Research Paper

Julia Eggers
Technical University of Munich
Munich, Germany
julia.eggers@tum.de

Andreas Hein
Technical University of Munich
Munich, Germany
andreas.hein@tum.de

Markus Böhm
University of Applied Sciences Landshut
Landshut, Germany
markus.boehm@haw-landshut.de

Helmut Krcmar
Technical University of Munich
Munich, Germany
helmut.krcmar@tum.de

Abstract

The success of mergers & acquisitions (M&A) depends on the buyer's adequate due diligence (DD) assessment of the target firm. Assessing the target's IT-enabled processes recently emerged as a novel information technology DD (IT DD) responsibility. However, it remains unclear how to operationalize and conduct the process assessment in IT DD. To address this challenge, we propose the big data analytics technology process mining (PM) and follow a design science research approach, based on literature and 12 interviews, to reveal and operationalize requirements for process assessment in IT DD, demonstrate PM to measure the operationalized requirements, and derive design principles and enabling factors to guide the design, implementation, and use of PM for process assessment in IT DD. Consequently, our study contributes to research on IT DD, M&A, and PM and provides practitioners with design knowledge and a prototypical PM artifact to leverage PM for process assessment in IT DD.

Keywords: Process mining, mergers & acquisitions, integration, IT due diligence, process measurement, design science

Introduction

In a world of rapid organizational and technological change, mergers and acquisitions (M&A) is an important strategy to ensure competitiveness. 2021 has been a record year for M&A, with the global volume reaching $5.1 trillion (PwC, 2022). But while the global M&A volume is rising, studies also show that M&A transactions are prone to high failure rates of 80% (Cartwright, 2013) in terms of meeting the expected financial goals and creating lasting value. This illustrates that many M&A transactions fail to realize the expected benefits, such as increasing efficiencies in scale and scope, acquiring external knowledge, and providing new product offerings (Berens, Mertes, et al., 2013).

One reason for frequent M&A failure rates is the buying firm's incomplete assessment of the target firm (Boeh, 2011). Thus, due diligence (DD) is considered an approach to decrease this risk by allowing the buyer to analyze and understand the target's situation and value creation before closing the deal (Lucks & Meckl, 2015). In particular, in the last decade, information technology due diligence (IT DD) has gained importance and is seen as fundamental for M&A success fueled by the digital transformation of industries and firms (Lucks & Meckl, 2015). During IT DD, the buyer is focused on learning about the target's IT infrastructure regarding the associated value, future reliability, opportunities, and risks (Koch & Menke, 2013). Recent reports from practice illustrate the increasing importance of IT DD (Zillmann, 2021; Zimmermann, 2018). For example, 80% of respondents in a survey among German M&A experts perceive the IT DD as a (very) important part of DD today, and 95% expect it to be in the future (Zimmermann, 2018). A primary reason for this trend lies in the increasing influence of the firm's "*digital maturity*" (Zimmermann, 2018, pp. 15-16) on firm performance, particularly in expanding digital industries, such as software, e-commerce, mobility, health, and service industries (Zillmann, 2021). Hence, assessing how the target's IT infrastructure enables operational excellence and business resilience is fundamental to navigating investment decisions (Zillmann, 2021; Zimmermann, 2018).

Because IT is increasingly interwoven with organizational value-creation processes (van der Aalst, 2016), buyers need to understand not only the target's IT infrastructure but also the underlying IT-enabled business processes to ensure M&A success (Henningsson & Yetton, 2013; Wilting & Pernegger, 2019). This need is underlined by a recent survey in which 66% of practitioners point toward the (very) high relevance of assessing the target's IT-enabled business processes as part of IT DD (Zimmermann, 2018). IT-enabled business processes refer to "*key business processes enabled or innovated by IT applications*," for example, IT-enabled customer service or supply chain processes (Qu et al., 2010, p. 98). The assessment of these IT-enabled processes is particularly relevant in the light of studies showing that the success of post-merger IT integration depends on a deep understanding of how the target's IT resources enable business processes and what opportunities and liabilities are associated (Boland et al., 2013; Henningsson & Yetton, 2013). Conversely, an inadequate understanding of the target's IT-enabled business processes during IT DD can lead to inadequate process and IT harmonization and integration, thus, resulting in detrimental effects on post-merger performance (Schönreiter, 2018). Hence, understanding the target's IT-enabled business processes in structure, performance, and implications for synergies, integration, and standardization is critical for M&A success (Henningsson & Yetton, 2013; Henningsson et al., 2019; Zillmann, 2021).

However, assessing the target's IT-enabled business processes was traditionally not considered part of the IT DD and came only recently into the focus of research and practice (Wilting & Pernegger, 2019). Accordingly, research on IT DD gives limited guidance on how and based on what information sources the buyer can assess the value of the target's IT-enabled business processes. This practical problem is accompanied by calls for future research on how IT DD can incorporate new areas of investigation, such as business process digitalization, automation, and standardization (Turuk & Moric Milovanovic, 2020; Wilting & Pernegger, 2019). In addition, information sources traditionally employed during IT DD, such as firm manuals, documentation, and employee interviews (Berens, Hoffjan, et al., 2013; Wilting & Pernegger, 2019), are limited in their capacity to provide comprehensive information that reflects the target's IT-enabled business processes as they are executed in reality, thus, increasing the risk of incomplete, outdated, or unnecessary information (Harvey & Lusch, 1995; Wright & Altimas, 2015). Consequently, it remains unclear how the IT DD can operationalize and assess the target's IT-enabled business processes.

Process mining (PM) represents a promising approach for discovering, monitoring and improving business processes by leveraging data that is already available in information systems (IS) and is increasingly used by organizations to reveal and understand their business processes (van der Aalst, 2016). To this end, PM not only allows for the in-depth analysis of processes in one firm but also for the cross-organizational, comparative analysis of similar processes in different organizations (van der Aalst et al., 2012). Consequently, by applying PM, organizations can learn about their own and another firm's processes as they are executed in reality (van der Aalst et al., 2012). Against this backdrop, we propose that PM might be a valuable approach to facilitate the assessment of IT-enabled business processes in the context of IT DD as it offers a data-driven, objective analysis of the target's processes while also enabling the comparative analysis of processes of the buy- and sell-side. In addition, as PM is agnostic to the source systems providing event logs, it can be applied to various IS at the target to illuminate the underlying business processes. Consequently, PM might overcome the limitations of existing assessment measures employed in IT DD that rely on subjective experiences and incomplete, manual documentation.

Nevertheless, studies on the organizational use of PM have only recently emerged, and the technology has not been studied in the context of M&A and IT DD thus far. We, therefore, pose the research question: *How can process mining support the assessment of IT-enabled business processes in the context of IT DD?*

To address this research question, we follow a design science research approach (DSR) (Hevner, 2007). Drawing on literature and 12 expert interviews, we (1) reveal and operationalize the requirements for process assessment in the context of IT DD (i.e., assessing process flow and complexity, the relevance of the process, financial and customer-oriented impact of the process, process digitalization and automation, conformance of buyer's and target's process, and standardization of the buyer's process), (2) demonstrate the applicability of PM to measure the operationalized requirements by implementing PM artifacts based on real data, and (3) derive eight design principles and four enabling factors to guide the design, implementation, and use of PM for process assessment in the context of IT DD. As a result, our study contributes to research on M&A and IT DD and the organizational use of PM and provides practitioners with design knowledge and a prototypical PM artifact to leverage PM for process assessment in IT DD.

Related Work

IT Due Diligence (IT DD)

While M&A transactions, in the broadest sense, encompass the transfer of ownership rights and control between firms—taking various forms from forming a joint venture to acquiring shares—our study focuses on the notion of M&A transactions as the combination of two firms in which, at least, one gives up economic independence (Miklitz, 2010). Following such a merger, the buying firm (the *buyer*) has to decide whether the divesting firm (the *target*) will operate as a relatively autonomous unit within the buying firm, will be integrated into the buying firm, or both firms will combine into a new firm (Ali-Yrkkö, 2002; Miklitz, 2010). Consequently, to proceed with an M&A transaction, the buyer must evaluate the target's business and anticipate potential post-merger integration (PMI) scenarios (Lucks & Meckl, 2015).

However, there is initial information asymmetry between the buyer and the target inherent to M&A transactions since the target has greater knowledge about the firm of interest than the potential buyer (Boeh, 2011). Hence, *DD* aims to reduce this information asymmetry by allowing the buyer to review information about the target and decide how to proceed with the transaction (Boeh, 2011). The DD review encompasses financial information, legal status, operating model, asset and business valuation, environmental conditions, management, human resources, and IT (Harvey & Lusch, 1995; Lucks & Meckl, 2015). Since organizations' value-creation processes are increasingly interwoven with and enabled by IT, the IT DD has gained importance in the last decade as a success factor in M&A (Lucks & Meckl, 2015). In particular, the IT DD allows the buyer to decrease information asymmetry grounded in the target's proprietary information about their IT organization, technologies, and processes (Wrede, 2021).

The *IT DD* refers to the buyer's analysis of the target's IT infrastructure in terms of associated value, future reliability, opportunities, and risks (Harvey & Lusch, 1995; Koch & Menke, 2013; Lucks & Meckl, 2015). As such, conducting IT DD serves primarily three goals, that is, (1) *risk and cost assessment*, (2) *benefit and synergy assessment*, and (3) *the development of integration scenarios*. First, the IT DD aims to estimate pre- and post-acquisition operating IT costs and the costs for the PMI IT project (Koch & Menke, 2013). Some identified costs can be risks or deal breakers, resulting in aborting the deal (Koch & Menke, 2013). Besides financial risks, the target's IT function can impose operational, legal, compliance, and dependency risks (Henke & Boller, 2016). Second, the IT DD yields insights into risks and opportunities in terms of synergy and restructuring potentials that are either directly rooted in the target's IT, such as lower infrastructure costs, or enabled by IT, such as reduced logistics costs through optimization of shipment processes (Boland et al., 2013). Third, the IT DD lays the foundation for PMI by developing and assessing integration scenarios concerning integration depth and compatibility with the buyer's IT landscape (Lucks & Meckl, 2015). The development of IT integration scenarios is facilitated by a deep understanding of how the target's IT resources enable their business processes (Henningsson & Yetton, 2013).

Assessment of IT-Enabled Business Processes in the Context of IT DD

The assessment of the target's IT-enabled business processes was traditionally not considered part of the IT DD (Wilting & Pernegger, 2019) until it became the focus of research and practice in recent years for two reasons. First, organizational value-creation is inextricably interwoven with IT, such that key business processes, for example, supply chain activities, customer service, or knowledge management, are increasingly enabled or innovated by IT (Qu et al., 2010). These processes are referred to as IT-enabled business processes (henceforth called *processes*) (Qu et al., 2010), and their efficiency, scalability, and design at the target are becoming important factors to consider when assessing the value of a potential M&A transaction (Wilting & Pernegger, 2019). Second, understanding the target's processes is required for designing and evaluating IT integration scenarios (Koch & Menke, 2013) since the buyer has to decide on either *renewing*, *taking over* one side's, *standardizing* similar, or *preserving* both sides' IT and processes for the newly formed firm (Wijnhoven et al., 2006). Consequently, research indicates that depending on the chosen integration approach, the inadequate harmonization and integration of the buyer's and target's processes in the—often time-pressured—PMI phase can have detrimental effects on the post-merger performance (Schönreiter, 2018). Hence, understanding the target's processes in terms of their structure, performance, and implications for PMI, such as opportunities for synergies, integration, and standardization, is a critical success factor for M&A (Henningsson & Yetton, 2013).

Nevertheless, research on IT DD gives only limited guidance on process assessment. Only recently, the first studies point toward additional focus areas in IT DD to account for process assessment. In particular, research suggests investigating the continuous support of business processes through IT and the cross-functional integration, performance, automation, and standardization of processes (Turuk & Moric Milovanovic, 2020; Wilting & Pernegger, 2019). However, research in this area is sparse and fragmented, so we lack a systematic understanding of operationalizing and conducting process assessment in the context of IT DD. This is exacerbated by the underlying lack of standardized key performance indicators (KPIs) to operationalize the goals of IT DD, such as synergies or risks (Boland et al., 2013; Koch & Menke, 2013).

In addition, it remains unclear what information sources the buyer can rely on to conduct the process assessment. Traditionally, IT DD draws, on the one hand, on documentation provided by the target, such as firm manuals, internal presentations, reports, and documentation of standard processes, and, on the other hand, on information acquired through personal exchange, such as employee interviews and observations (Berens, Hoffjan, et al., 2013; Wilting & Pernegger, 2019). However, both information sources are limited in providing objective, comprehensive information that reflects processes as they are executed in reality, thus, increasing the risk of incomplete, outdated, or unnecessary information (Harvey & Lusch, 1995; Wright & Altimas, 2015). In particular, business process management (BPM) research cautions about the limited value of manually crafted process documentation or personal insights to assess organizational processes since these tend to reflect idealized processes and experiences disconnected from reality (Kohlbacher & Gruenwald, 2011; van der Aalst, 2016).

In sum, assessing the target's processes and their implications on the PMI recently emerged as critical factors for buyers to consider during IT DD. However, the approach to and operationalization of process assessment in the context of IT DD remains unclear. In addition, traditional approaches to IT DD are limited in the comprehensiveness of their results. Against this backdrop, scholars from the IT DD field have called for exploring novel approaches to support IT DD and, in particular, process assessment (Wilting & Pernegger, 2019). To this end, a promising approach might emerge from the field of process analytics.

Process Mining (PM)

PM is a relatively young big data analytics technology aimed at discovering, monitoring, and improving business processes by leveraging data that are already available in organizations' IS (van der Aalst, 2016). It is rooted in machine learning and data mining on the one hand and process modeling and analysis on the other hand. Building on these disciplines, PM allows for not only a KPI-oriented view of organizations but also a process-oriented method of evaluating and advancing organizations by establishing a link between real processes and process models (van der Aalst, 2016).

To this end, PM leverages the digital traces found in IS as every activity performed in the system is sequentially recorded in its databases as an event (van der Aalst et al., 2012). These events can be used to reconstruct *event logs* that represent the processes as they happen in the firm's IS in reality. Therefore, each event must relate to an activity, that is, a well-defined step in the process, and to a case, that is, a specific instance of the process, such as an order or invoice (van der Aalst, 2016). Moreover, any kind of additional information related to the cases can be logged and analyzed, for example, the user who executed an event or the cost associated with the process step (van der Aalst et al., 2012). Organizations can use these event logs to perform three basic types of PM. First, organizations can *discover* the actual flow of processes without having any knowledge of the processes beforehand. Second, organizations can *check the conformance* of actual processes with a desired process model. Third, they can *enhance* already existing process models to encompass characteristics of the discovered real process (van der Aalst, 2016).

Since PM only emerged in the mid-90s, research thus far has primarily focused on advancing the technological basis, such as improving the design of discovery algorithms and event logs (Thiede et al., 2018), while only recently the organizational use of PM came into focus (Badakhshan et al., 2022). In this light, studies have shown that PM is increasingly used by organizations across industries, such as public administration, production, and healthcare (Thiede et al., 2018), and for various processes, ranging from standardized sub-processes in accounting to customized end-to-end processes across the supply chain (Eggers et al., 2021). In addition, studies report on the implementation of PM for specific use cases, that is, applying PM to a specific process with specific goals, such as uncovering fraudulent activities in auditing (Jans et al., 2014) or measuring process performance in manufacturing (Lau et al., 2009). While the research focuses on single PM use cases in single organizations and provides deep insights into the structure and value of specific processes, scholars from the field of PM point toward the additional potential of PM to assess processes across organizations (van der Aalst et al., 2012).

This approach is referred to as *cross-organizational PM*. It allows for either the analysis of cross-organizational processes in a *collaborative setting*, that is, multiple organizations are involved in the same process, such as in a supply chain, or the analysis of cross-organizational processes in a *comparative setting*, that is, multiple organizations each perform (variations of) the same process such as administrative processes in multiple municipalities (van der Aalst et al., 2012). By applying PM in cross-organizational settings, organizations can compare processes, learn from one another, and identify variations, best practices, and root causes for weaknesses (van der Aalst et al., 2012). Despite the indisputable potential of cross-organizational PM, its application in research and practice remains scarce (Thiede et al., 2018), with a few notable exceptions comparing similar healthcare processes across hospitals (Partington et al., 2015) or analyzing cross-organizational production processes (Tönnissen & Teuteberg, 2019).

Method

Overall Research Approach

Our study was motivated by the observation that even though buyers in the context of M&A transactions need to assess the target's (IT-enabled) processes to account for the ever-increasing importance of digitalized operations, the IT DD as the pre-deal analysis of the target's IT infrastructure does not account for assessing the target's (IT-enabled) processes. As the assessment of processes only recently came into the focus of IT DD, research lacks insights on how to operationalize and conduct the process assessment. Addressing this shortcoming, our study employs DSR to ensure practical relevance and scientific rigor (Hevner, 2007) while developing a novel, useful *IT artifact* based on PM for supporting the process assessment in IT DD and *design knowledge* to guide the artifact's construction by specifying the relationship between the problem and solution space (Baskerville et al., 2018). Thus, our study follows one of the core principles of IS research, which is to generate knowledge about how the application of IT can address organizational problems (Hevner et al., 2004).

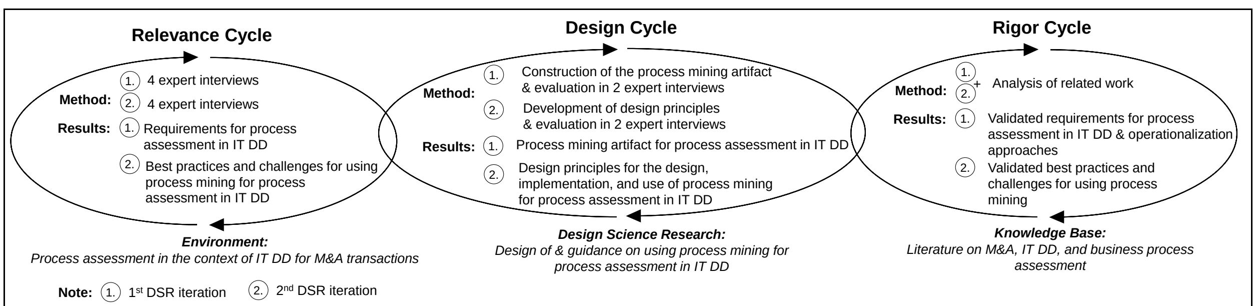

Figure 1. DSR research approach (own representation based on Löhe and Legner (2014) and Hevner (2007))

To this end, we iteratively follow the three cycles of design DSR (see Figure 1), that is, the *relevance cycle* to connect our study with real-world problems, i.e., process assessment in the context of IT DD, the *rigor cycle* to incorporate the existing knowledge base, i.e., knowledge on IT DD and techniques for process assessment, and the *design cycle* to develop and evaluate our IT artifact and the corresponding design knowledge (Hevner, 2007). We conducted two iterations of all three cycles. In the first iteration, we focused on designing PM analyses for process assessment in IT DD based on an in-depth understanding of the underlying requirements from literature and practice. In the second iteration, we focused on deriving design principles to guide the design and use of PM for process assessment in IT DD.

First DSR Iteration

The first DSR iteration focused on designing PM analyses to support process assessment in the context of IT DD. To this end, as there is only scant knowledge about process assessment in IT DD in the literature, we started the first DSR iteration with the *relevance cycle* to develop an in-depth understanding of the requirements. As expert interviews are an established method to analyze problems in DSR (Österle et al., 2011), we conducted four semi-structured interviews (Myers & Newman, 2007) with experts from the field of IT DD who had each conducted between five and 30 IT DDs in their careers (see Table 1 for an overview of all interviews conducted in the DSR). The interviews mainly focused on the interviewees' experience in IT DD, what information sources and tools they rely on to perform IT DD, how they currently approach the analysis of the target's processes in the context of IT DD, what challenges they experience, and how they wished to be supported. The interviews were conducted by phone due to geographical restrictions on the interviewees' side and in German, the native language of the interviewees, but we translated quotes into English for the purpose of this article. After transcribing the 263 minutes of taped interviews, we analyzed the qualitative data based on an inductive coding approach (Gioia et al., 2013) to understand the requirements for process assessment in IT DD. Throughout the analysis procedure, by relating similar codes to establish concepts (Gioia et al., 2013), six requirements emerged, that is, understanding the target's *process flow and complexity*, the *relevance of the process*, *financial and customer-oriented impact* of the process, *digitalization and automation* of the process, *conformance* between the buyer's and target's process, and *standardization* of the buyer's process.

Next, we initiated the *rigor cycle* to validate the identified requirements for process assessment in IT DD grounded in literature. In addition to related work from the field of M&A and IT DD, we also accounted for books and grey literature from practitioners in the domain of M&A and IT DD to comprehensively understand the requirements for process assessment. The literature analysis confirmed the requirements identified in the relevance cycle; for example, the literature showed that the assessment of process complexity in terms of variety and duration should be acknowledged in IT DD (Wright & Altimas, 2015), which relates to the requirement of understanding the target's process flow and complexity expressed by the experts, or that the comparison of the target's and buyer's processes facilitates IT DD (Koch & Menke, 2013), which relates to the requirement of understanding conformance between the buyer's and target's processes expressed by the experts.

Building on the validated requirements for process assessment in IT DD, we then engaged with literature on business process assessment to operationalize the requirements. While there is a lack of guidance on operationalizing process assessment in IT DD, the field of BPM has long studied how to measure business processes (Leyer et al., 2015). To this end, business process measurement is concerned with "*the continuous observation of predetermined performance indicators for the purpose of attaining process targets*" (Leyer et al., 2015, p. 227). Importantly, process performance is a multi-dimensional construct that requires the integration of different performance indicators (Leyer et al., 2015). Acknowledging the need for multi-dimensional measurement and the fragmented landscape of process performance indicators, we drew on the most recent literature review by van Looy and Shafagatova (2016). This study synthesizes the current body of knowledge on process performance indicators by operationalizing and categorizing them based on the Balanced Scorecard (BSC) (Kaplan & Norton, 1996) as a well-established approach to organizational performance measurement that considers the dimensions of *financial*, *customer*, and *internal business process* performance, and performance related to *learning and growth*. Drawing on the framework of operationalized process performance indicators (van Looy & Shafagatova, 2016), we then operationalized the identified requirements for process assessment in IT DD.

First, we selected and, if necessary, adapted process performance indicators from the framework corresponding to the identified requirements, such as the indicator *on time delivery rate* to operationalize the performance of customer-centric processes or *conformance to specifications* to operationalize the degree of process standardization. During the procedure, it emerged that the identified requirements and selected indicators correspond to the dimensions of process performance proposed by the framework (van Looy & Shafagatova, 2016), allowing us to structure the requirements and indicators. In particular, the *flow* and *relevance* of the process are reflected in the internal process performance, the *financial and customer-oriented impact* of processes is reflected in the financial and customer performance, and the *digitalization, automation, and scalability* of the process are reflected in the learning and growth performance. In addition, since the dimensions primarily focus on process performance, we inductively identified the need for a further dimension in IT DD that does not measure process performance but *conformance*, reflecting the conformance of similar processes at the buyer and target. The comprehensive list of operationalized requirements for process assessment in IT DD is presented in the first results chapter.

Last, we engaged in the *design cycle* to design PM analyses that meet the requirements for process assessment in IT DD identified in the relevance cycle and based on the operationalization derived in the rigor cycle. We implemented the analyses employing real process data from four organizations using the Celonis PM software. The second results chapter presents details on the data and the analyses. Concluding the design cycle, we conducted evaluation interviews with two experts that lasted 169 minutes. The interviews encompassed a presentation of the implemented PM analyses and expert feedback regarding efficacy, quality, and utility (Hevner et al., 2004). The qualitative analysis of the interviews indicated the need for additional process KPIs, particularly *financial volume affected by late deliveries* and *late invoices,* to show process impact on the target's working capital as a relevant factor of M&A deal negotiation.

Interviewee	Role	Experience	Duration	DSR Iteration
Expert A	Senior Consultant Transaction Advisory	15 IT DDs	90 mins.	1st
Expert B	Senior Manager Transaction Advisory	30 IT DDs	90 mins.	1st
Expert C	Partner and Director of IT Audits	5 IT DDs	41 mins.	1st
Expert D	Senior Manager Transaction Advisory	20 IT DDs	42 mins.	1st
Expert E	Consultant IT M&A	5 IT DDs	59 mins.	2nd
Expert F	Consultant Transaction Advisory	20 IT DDs	45 mins.	2nd
Expert G	Director of IT Consulting	>100 IT DDs	62 mins.	2nd
Expert H	Senior Manager Technology M&A	>80 IT DDs	60 mins.	2nd
Expert A	Senior Consultant Transaction Advisory	15 IT DDs	85 mins.	1st (evaluation)
Expert B	Senior Manager Transaction Advisory	30 IT DDs	84 mins.	1st (evaluation)
Expert E	Consultant IT M&A	5 IT DDs	36 mins.	2nd (evaluation)
Expert I	Process Mining Specialist	>25 PM impl. projects	42 mins.	2nd (evaluation)

Table 1. Overview of the expert interviews conducted in the DSR approach

Second DSR Iteration

The second DSR iteration focused on deriving design principles (Gregor et al., 2020) to guide the design and use of PM for process assessment in IT DD. We started with the *relevance cycle* by conducting additional six semi-structured interviews (Myers & Newman, 2007) with experts from the field of IT DD who had conducted between five and over 100 IT DDs in their careers. The interviews focused on the interviewees' experience in IT DD, their experience with using PM or other BDA techniques in the context of IT DD, and potential challenges and best practices when designing, implementing, and using PM for IT DD. If the interviewees were inexperienced with PM, we presented them with the implemented analyses from the first DSR iteration. Again, the interviews were conducted via phone and in German, with quotes being translated for this article. After transcribing the 226 minutes of taped interviews, we analyzed the qualitative data based on an inductive coding approach (Gioia et al., 2013) to reveal best practices and guidelines for leveraging PM for process assessment in IT DD. Four enabling factors emerged from the analysis: *establishing pre-deal exclusiveness*, *prioritizing processes*, *jointly evaluating analyses*, and *accounting for synergies with other DD streams*. In addition, the experts emphasized the importance of designing *cross-organizational PM analyses* where possible and ensuring *data access* at the target.

We then initiated the *rigor cycle* to validate and complement the best practices identified in the relevance cycle. Since no prior research reports on the use of PM for IT DD, we relied on related literature about the organizational use of PM to identify principles for PM implementation. In particular, the analysis revealed the importance of *data anonymization* for PM in sensitive settings, such as the pre-deal M&A phase, and the need for *merging process data* for performing cross-organizational PM analyses.

In the *design cycle*, iterating between the results from the rigor and relevance cycles and informed by the operationalized and implemented PM analyses from the first DSR iteration, we synthesized the emerging knowledge in eight design principles (Gregor et al., 2020) and four enabling factors to guide the design and use of PM for process assessment in IT DD. We evaluated the resulting design knowledge in two additional interviews with IT DD and PM experts. The third results chapter presents the final results.

Results

Operationalization of Process Assessment in IT DD

In the first cycle of our DSR approach, we inductively synthesized and operationalized buyers' requirements for assessing the target's processes in IT DD based on insights from related work and expert interviews (see Figure 2). The operationalized requirements then served for the first design cycle, which yielded the prototypical implementation of PM analyses for IT DD. We briefly outline the identified requirements and their operationalization in the following.

Dimensions of Process Assessment	Process Assessment Indicators*	Requirements for Process Assessement in the Context of IT DD*
Internal Process Performance (van Looy & Shafagatova, 2016)	Process model incl. process variants Number of cases in the system Average process cycle time	• „[…] how is the **process supported by the systems**?“ (Expert A) • **Complexity** of the target‘s processes in terms of variety and duration (Wright & Altimas 2015)
	Number of process users Average number of users per day Manual users per case Cases per manual user	• „[…] **how many users** are regularly using the systems? That is relevant for licensing.“ (Expert C) • **Relevance** of the target‘s systems in terms of their use (Koch & Menke 2013)
Financial & Customer Performance (van Looy & Shafagatova, 2016)	Financial volume processed On time delivery rate Invoicing cycle time Financial volume affected by late deliveries Financial volume affected by late invoicing	• Identification of the target‘s key processes based on **financial volume** (Wright & Altimas (2015) • „[…] we want to see how the target‘s process is creating **value** and **satisfaction for the customer**“ (Expert B) • Performance of the target‘s **customer-centric** processes (Andriole 2007)
Learning & Growth Performance (van Looy & Shafagatova, 2016)	Overall automation rate Automation rate per activity Overall manual change rate Overall change rate Overall rework rate	• „[…] we need a standardized way of measuring the target‘s rate of **process digitalization** and **automation**“ (Expert B) • Process automation and digitalization (Wilting & Pernegger 2019) • „[…] identify **best practices** to increase the the **efficiency** and production **volume** of the buyer“ (Expert C) • „[…] currently we don‘t have the information to assess **whether a process is automated in what system**“ (Expert B) • „[…] evaluating **how well the target‘s process steps are digitalized** is a core question of IT DD“ (Expert B)
Conformance (inductive)	Number of target-side cases conforming to buy-side processes Number of conformance violations of target- and buy-side processes Type of conformance violations of target- and buy-side processes	• „[…] understand the target‘s ERP system use in terms of **conformance with the buyer‘s processes**“ (Expert A) • **Comparison** of target and buyer’s processes (Koch & Menke 2013) • „[…] identify the **faster, more efficient process** by comparing buyer and target“ (Expert C) • „[…] we want to analyze **synergies** due to cost savings that can be achieved by integrating the target’s ERP or CRM systems into the buyer’s” (Expert D)
	Number of buy-side cases conforming to standard process model Number of buy-side conformance violations with standard process model Type of conformance violations of buy-side processes and standard process model	• „[…] not every buyer has documentation of their own processes ready, so sometimes it might even be necessary to **conduct an “IT DD light” on the buyer’s side**” (Expert D)

*based on van Looy & Shafagatova (2016) and inductively derived from the expert interviews

*inductively derived from the literature analysis and expert interviews

Figure 2. Framework of indicators for the assessment of IT-enabled business processes in the context of IT DD

During IT DD, the buyer intends to assess the target's process landscape to reveal potential process-related risks, opportunities, and synergies for the impending M&A deal. First, the buyer wants to understand the target's *process flow and complexity* regarding process variants and case volume, cycle times, and support by the underlying IT to develop a basic understanding of the target's process landscape. In addition, analyzing the process landscape should reveal the target's best practice process designs, for example allowing for more efficient throughput times or higher production volume, that could be valuable for the buyer to adopt. Second, the buyer is interested in the *relevance of the process* in terms of regular users in the process. This indicates whether the process will likely continue after the PMI and supports the estimation of necessary licenses for the underlying IT. Third, the buyer intends to evaluate the *financial and customer-oriented impact of the process* in terms of financial volume processed and implications of the process performance for the customer, for example, related to customer satisfaction, to assess how the process contributes to value creation. Fourth, the buyer must understand the target's *process digitalization and automation* to determine the target's degree of digitalization and potential for learning about and acquiring best practices for efficient, scalable, and adaptable operations. Fifth, the buyer is interested in developing process integration scenarios by *comparing similar processes at the buyer and target* to reveal the degree of standardization, deviations, and synergies as factors influencing PMI. Last, the buyer aims to analyze their *process landscape in terms of standardization* to identify risks for PMI.

The identified requirements were then operationalized to enable the assessment of processes in IT DD. To this end, each requirement is reflected in multiple process performance indicators derived from the process performance framework of van Looy and Shafagatova (2016) and inductively from the expert interviews. For example, the *process flow and complexity* are operationalized through the discovery of the corresponding process model and its variants, the number of cases in the system, and the average process cycle time. In contrast, the *comparison of the buyer's and target's process landscape* for the purpose of process integration scenarios is operationalized through the number and types of conformance violations between similar processes at the buyer and target. The identified requirements and their operationalization are structured along the dimensions of process performance as indicated by van Looy and Shafagatova (2016), that is, *internal business process performance*, *financial & customer performance*, and *learning & growth performance* as well as the inductively identified dimension of process *conformance*. The comprehensive operationalization is displayed in Figure 2.

Demonstration of Process Assessment with Process Mining in IT DD

Building on the framework of indicators that resulted from the first rigor and relevance cycles, we then engaged in the first design cycle by developing prototypical PM analyses to demonstrate the applicability of PM for process assessment in IT DD. The demonstration is based on real, anonymized process data from four organizations (see Table 2) that we used for two M&A scenarios. The first scenario is based on the order-to-cash (O2C) process data of Company A (buyer) and B (target) from the German mechanical engineering sector. The second scenario is based on purchase-to-pay (P2P) process data of Company C (buyer) and D (target) from the engineering industry. In all cases, data originated from the companies' ERP system, i.e., SAP S/4 HANA. We decided to focus on O2C and P2P as organizational core processes that prevail across industries to enhance the transferability of our results. In addition, we chose to analyze the O2C, respectively, P2P processes of buyer and target in cross-organizational PM analyses to facilitate the comparison of buyer and target. Thus, in both scenarios, the buyer and target process data were merged into one combined data model serving as the basis for the PM analyses. Building on the framework of indicators that we developed earlier, we implemented multiple analyses for each scenario reflecting the four dimensions of process assessment (see Figure 2) in the Celonis PM software using the same process performance indicators for the buyer (right side of the analysis) and the target (left side of the analysis). It is to be noted that, except for the conformance analysis, the analyses could also be performed separately.

Name	Industry	Revenue/2016	Role	Process	Dataset size	Dataset timeframe
Company A	Mechanical engi.	>$4 billion	Buyer	O2C	1,480,000 cases	07/2016-05/2017
Company B	Mechanical engi.	>$200 million	Target	O2C	132,000 cases	06/2016-05/2017
Company C	Engineering	>$200 million	Buyer	P2P	191,000 cases	02/2016-03/2017
Company D	Engineering	>$200 million	Target	P2P	885,000 cases	09/2016-10/2017

Table 2. Datasets used for demonstrating the process mining analyses

For the sake of brevity, we will only illustrate the demonstration by highlighting relevant results from the analysis of *internal process performance*, *conformance*, and *learning & growth performance*.

Internal Process Performance

The PM analysis of the *internal process performance* consists of a comparison of the buyer's and target's *process flow and complexity*, enabled by the discovery of the process graphs, process variety, volume, and duration, and the comparison of the *relevance of the process* at buyer and target, enabled by the analysis of the number of users and cases in the system. Accordingly, Figure 3 illustrates the comparison of the buyer's and target's *process flow and complexity* in the cross-organizational PM analysis for the O2C scenario. As evident from the analysis, the buyer's O2C process (right side)—happening for over 1.4 million orders logged in the system for the specific time period—presents as rather streamlined with 5,100 distinct process variants. Conversely, the target (left side)—handling only 132,000 orders in the specified time period—demonstrates over 25,000 different variants of executing its O2C process in the ERP system.

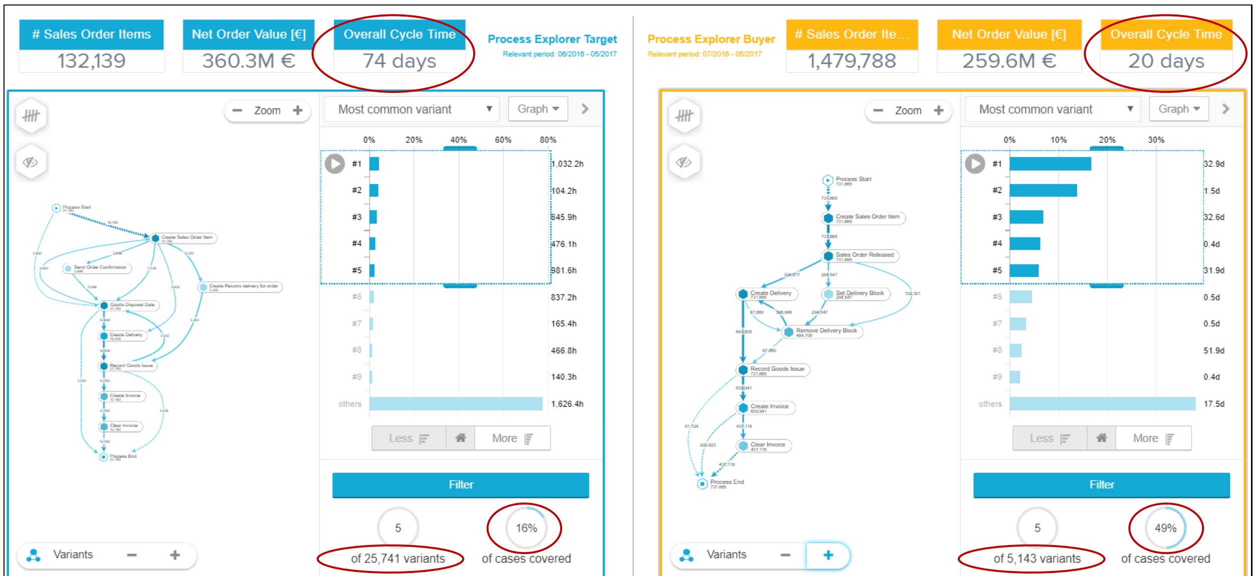

Figure 3. Process mining analysis for the *internal process performance* dimension for the O2C process of buyer and target

While the five most common process variants for the buyer represent how nearly 50% of its orders are processed, the same number of variants covers just 16% of the orders in the target's system. This indicates a highly specialized O2C process on the target's side, resulting in a considerably longer sales cycle of 74 days compared to 20 days at the buyer. This raises critical questions about how the target's process can be integrated into the buyer's process and the underlying IT. Can the buyer's IT support the target's specialized process variants? Would it be advisable first to standardize the target's processes in a standalone solution and only integrate it after the number of variants has decreased? By doing so, could the sales cycle of the target be accelerated so that synergies in terms of process efficiency could be realized through the merger?

Conformance

The PM analysis of the *conformance dimension* aims at understanding the rules that the respective business processes of the buyer and the target follow and whether and how they align. Figure 4 shows the conformance check results for the conformance of the target's O2C process to the buyer's O2C process.

The target's O2C process shows conformity to the buyer's most common O2C process variants (covering 80% of its cases) for only 34% of the sales orders. With over 80 different violations of conformance to the buyer's O2C process occurring, the non-conformant process flows also take considerably longer (81 days with violations compared to 62 days without violations), and each case requires a larger number of processing steps (almost 10 steps with violations compared to 6 steps without violations). To shed more light on the violatisons, the analysis presents the buyer with a breakdown of which of the target's activities are non-conformant with the standard process and how often they occur. Drawing on this information, the buyer can investigate the non-conformant activities that are not supported by the buyer's IT to determine if they are required and should be accounted for in the PMI or if these activities should not be part of the integrated process landscape. If the analysis points toward keeping the process in the PMI, as a next step, the buyer could define measures and estimate costs for standardizing the target's current system in a standalone approach for preparing the integration. An alternative approach could be to keep the buyer's and target's systems standalone and operate two independent platforms with their own standard processes.

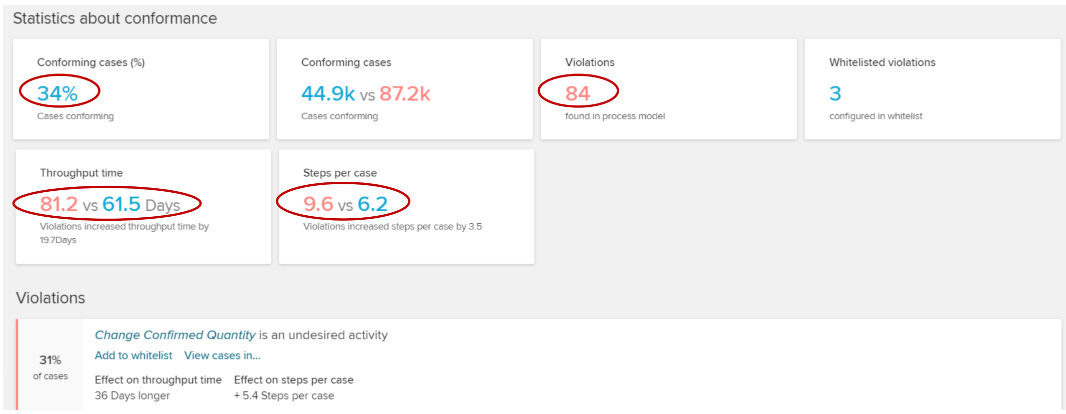

Figure 4. Process mining *conformance* analysis of the buyer's and target's O2C processes

Learning & Growth Performance

The PM analysis of the *learning & growth performance* dimension investigates the automation and digitalization efforts of the buyer and target in comparison. Accordingly, Figure 5 illustrates the cross-organizational analysis of the buyer's and target's P2P processes. It shows that the target's overall low automation rate is at just 1% compared to the buyer's 6% automation rate, with automation being calculated as the share of process steps executed by an automated system user. Additionally, the table below indicates all activities included in the organizations' P2P processes, along with the respective automation rate.

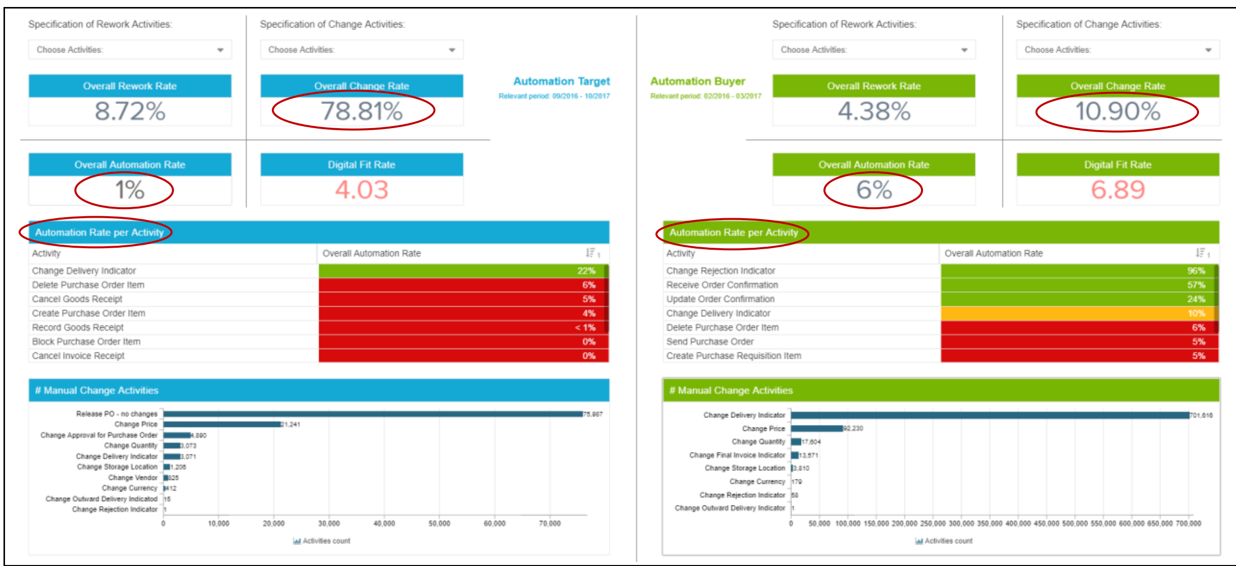

Figure 5. Process mining analysis of the *learning & growth* performance dimension of the buyer's and target's P2P processes

Based on this information, the buyer can identify activities that are already well automated—which could imply potential best practices and synergies to leverage during the integration—and activities with the potential to be automated. Ideally, the buyer and target are complementary in the automation of certain activities so that during the integration, the automation of the future firm can be optimized. Additionally, the manual change and rework rate are indicators of the firm's process efficiency and scalability. Rework includes activities such as cancellations or deletions of orders which ultimately cause all actions performed up to this step to be futile. Change activities refer to any action that changes the state of an order after it has been created, which leads to longer and more costly sales cycles. The analysis shows that the target has a high manual change rate of almost 79% (compared to 11% at the buyer). Hence, the buyer might investigate why these frequent changes are necessary and whether the target's IT is not designed in accordance with the real process flow, possibly threatening the integration.

Design Principles for Process Assessment with Process Mining in IT DD

Based on our operationalization, demonstration, and evaluation of PM for process assessment in IT DD that resulted from the first DSR cycle, we focused the second DSR cycle on developing design principles to provide prescriptive knowledge to scholars and practitioners for the design, implementation, and use of PM analyses for IT DD. Informed by literature and additional expert interviews, we derived eight design principles for the design and implementation of PM in IT DD and four additional enabling factors (see Figure 6).

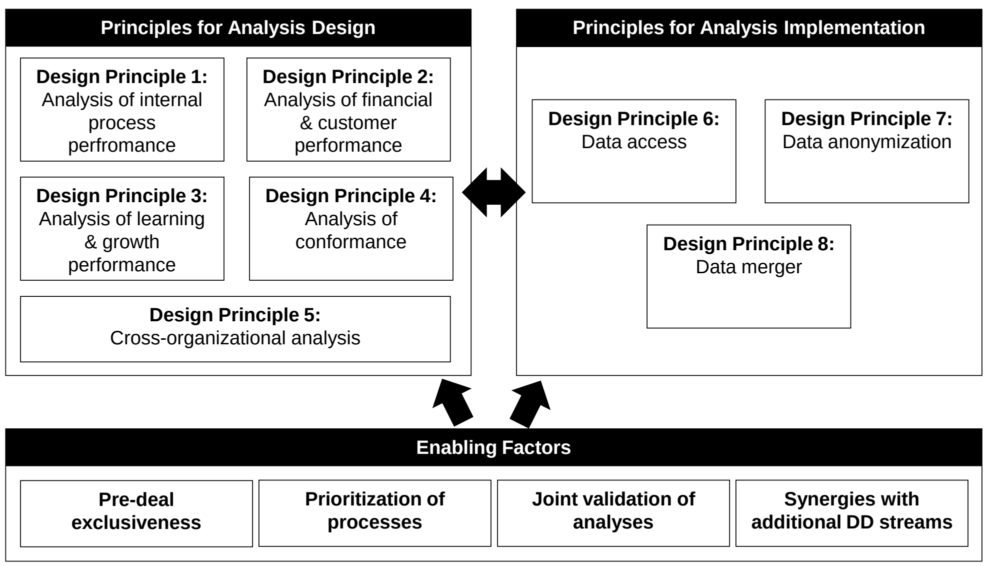

Figure 6. Design principles and enabling factors for the design and implementation of process mining for process assessment in IT DD

First, we propose five design principles for designing PM analyses for process assessment in IT DD. *Design Principle 1* recommends that the buyer gain insights into the target's internal process performance regarding process complexity, relevance, and flow by designing PM analyses to discover the process model, variants, volume, cycle times, and users. Incorporating these indicators in PM analyses establishes an overview of the target's process landscape. Additionally, it is "*extremely valuable for the buyer to direct the focus toward critical process areas that require improvement or standardization, that are non-conformant to regulations and could become a liability or that, in contrast, are suitable for integration*" (Expert E). As the buyer often intends to grow their operations after the M&A transaction is finalized, it has become "*a fundamental requirement of buyers to understand the flow and performance of the target's internal processes*" (Expert F) which, however, was traditionally difficult to measure due to a lack of data and analytical tools (Expert E).

Design Principle 2 advises the buyer to determine the financial and customer-oriented impact of the target's processes by designing PM analyses measuring the financial volume handled in the process, the financial volume impacted by late activities, and the impact of invoicing and delivery times on the customer.

Evaluating these indicators with PM allows the buyer to understand how the target's processes influence their financial situation and customer satisfaction, which is of interest for negotiating the deal volume. In particular, the deal volume depends on, for example, future investments required to optimize processes detrimental to the working capital or negatively influencing the customer experience (Expert F). This is illustrated by an account of Expert G, who implemented PM in the context of IT DD. The analyses revealed that the target frequently failed to realize early payment discounts. When discussing these results with the target, they disclosed purposefully withholding payments to increase liquidity, which could have skewed the negotiated deal volume.

Design Principle 3 proposes the buyer assess the potential for growing and learning from the target in terms of process digitalization and automation by designing PM analyses that measure the overall and activity-specific automation rate and rework and manual change rates. Analyzing these indicators with PM allows the buyer to determine the target's status of digitalization and potential for acquiring superior process knowledge, such as process automation, that will benefit the future merged firm. For instance, one expert pointed out how the PM analyses would have supported a buyer from the pharmaceutical industry "*who were interested in acquiring a German plant to learn about their highly automated and optimized processes*" (Expert G).

Design Principle 4 recommends that the buyer develop process integration scenarios by designing PM analyses that measure the conformance of similar processes at the buyer and target. Through evaluating the process conformance between buyer and target, the buyer can "*determine which of the target's processes can be supported by the buyer's systems or vice versa, and which processes share enough similarities to be integrated during the PMI*" (Expert E). As a result, the conformance analysis allows for the identification of synergies but also integration risks. Accordingly, the buyer and the target both have potential profit from the analyses. Awareness of synergies allows the target to increase the price and the buyer to pay a premium on the deal volume (Expert F). This can differentiate between losing and closing the deal, especially if several buyers are interested in the target, outbidding each other (Expert E).

Design Principle 5 advises the buyer to facilitate the use of PM as outlined before by designing the analyses in a cross-organizational approach for benchmarking the buyer's and target's processes. Even though all PM analyses can be implemented separately, the demonstration showed that the cross-organizational PM analysis with the same indicators of the same process at buyer and target allows for "*the identification of key similarities and differences of the processes at a glance, while without PM we either don't have the database to derive such insights at all or we have various, potentially inaccurate, documents*" (Expert G).

In addition to principles for designing PM analyses for process assessment in IT DD, we derived three design principles for guiding the implementation. To this end, *Design Principles 6, 7, and 8* recommend that the buyer ensure access to the required process data by identifying corresponding source systems at the target, anonymizing the data, and—where possible—merging them with the buyer's data of a similar process into one data model to facilitate comparability. Depending on the source systems, the access to and pre-processing of process data can be uncomplicated, such as for "*commons SAP systems that support the firm's core processes and rely on a standardized data structure, so that accessing, preparing and integrating the data can be done quickly*" (Expert I). However, merging data from different source systems might result in technical as well as conceptual challenges when comparing the processes, which requires more elaborate PM techniques (van der Aalst et al., 2015). In addition, the target might be reluctant to share their process data due to the sensitivity of the information, which can be addressed through data anonymization or privacy-preserving algorithmic techniques (Mannhardt et al., 2019).

Last, we identified additional enabling factors that support buyers in applying PM in IT DD. First, complications with accessing the target's process data can be alleviated with contractual measures, such as establishing a degree of *pre-deal exclusiveness* that minimizes the target's risk when sharing sensitive data, which can also facilitate an open dialogue between buyer and target when preparing, performing, and evaluating the PM analyses. This dialogue is particularly valuable for identifying and *prioritizing critical processes* at the target prior to the analyses. As the IT DD usually is performed in a limited timeframe, concentrating analysis efforts on particular areas of interest for the buyer increases the likelihood of creating valuable insights. In addition, joint *validation meetings* between the buyer and target after the analyses have been performed to discuss and interpret the results can contribute toward understanding their implications on the M&A transaction. Finally, the experts pointed toward the importance of leveraging the PM analyses for synergies with other DD areas, such as operational DD and financial DD, that can, on the one hand, contribute knowledge to deriving implications from the analyses and, on the other hand, can enhance their assessments with findings from PM.

Discussion and Limitations

Our study was motivated by the observation that we currently lack knowledge on assessing the target's processes in the context of IT DD, even though process assessment is becoming an increasingly important part of IT DD. Addressing this challenge, we engaged in a DSR approach and (1) revealed and operationalized the requirements for process assessment in the context of IT DD, (2) demonstrated the applicability of PM to measure the operationalized requirements by implementing PM artifacts based on real data, and (3) derived eight design principles and four enabling factors to guide the design, implementation, and use of PM for process assessment in the context of IT DD. In the following, we discuss the implications and contributions of our findings to research and practice and their limitations.

First, we contribute to research on IT DD (Harvey & Lusch, 1995; Koch & Menke, 2013) by revealing and operationalizing thus far largely unknown requirements for process assessment in IT DD and by presenting PM as a tool for execution. Even though research in recent years has acknowledged the importance of assessing the target's IT-enabled processes as part of IT DD (Wilting & Pernegger, 2019) to account for the relevance of IT-enabled processes for organizational and PMI performance (Henningsson & Yetton, 2013; Schönreiter, 2018), thus far, we lacked an understanding of how to conduct and operationalize the assessment. To this end, drawing on insights from literature and practice, we reveal dimensions and corresponding indicators to assess the target's processes in the context of IT DD. As a result, we create a more nuanced understanding of IT DD as not only the assessment of the target's IT infrastructure but as the assessment of the target's IT infrastructure *and enabled processes* to reflect their inextricable interrelations in contemporary organizations. In addition, we demonstrate PM as a suitable IT artifact to execute the assessment while overcoming the limitations in comprehensiveness and objectivity of traditional information sources in IT DD, such as documentation and employee interviews (Wright & Altimas, 2015). In contrast, PM provides data-based, objective insights that reflect the reality of the target's processes, thereby introducing unprecedented transparency to the IT DD. These results resonate with prior research pointing toward the potential of BDA technologies to aid decision-makers in M&A transactions through increased transparency (Lau et al., 2012). Our study showed that the transparency introduced through PM might benefit the buyer and the target, as it allows highlighting opportunities grounded in the target's processes, such as efficient production processes, that warrant a higher deal volume. Concurrently, the PM analysis might shed light on process-related risks that the target would prefer not to disclose. As a result, we encourage scholars to study how the use of analytics technologies such as PM in IT DD changes the collaboration and negotiation patterns in the pre-deal phase.

Second, we contribute to research on the role of IT in M&A (Henningsson et al., 2019) as we demonstrate cross-organizational PM as a technique to support the development of post-merger IT integration scenarios by revealing alignment between the target's IT and their business processes as well as opportunities and risks for the integration of the buyer's and target's processes. In particular, research on M&A points toward the importance of business-IT alignment for the success of post-merger IT integration, which is reflected by how the newly formed firm's IT enables its business processes (Mehta & Hirschheim, 2007). However, developing and evaluating scenarios of how business-IT alignment and IT integration will unfold in the newly formed firm is considered challenging and requires the systematic assessment of what side provides the "better" IT and processes, which currently lacks systematic guidance (Schönreiter, 2018). To this end, we introduce cross-organizational PM as a technique to measure the support of the target's and buyer's business processes through IT as well as the performance, automation, standardization, and conformance of their processes. Scholars in the field of M&A might leverage these data-driven insights to explore how different configurations of business-IT alignment on the buyer and target side can be incorporated into integration scenarios and how different integration scenarios impact PMI performance. Accordingly, we also encourage scholars to investigate the potential of applying PM to the PMI phase.

Third, we contribute to research on the organizational use of PM (Badakhshan et al., 2022; Thiede et al., 2018) by providing a PM artifact, design principles, and enabling factors for the design, implementation, and use of PM in the context of IT DD. While early research on PM focused primarily on advancing the technological basis, only recently, the organizational use of PM came into research focus (Badakhshan et al., 2022). Still, the cross-organizational use of PM, for example, to compare processes across organizations, has received scant attention in research thus far (Thiede et al., 2018). Thus, we provide insights into the design, implementation, and use of cross-organizational PM analyses grounded in real process data and based on validated requirements. In particular, we demonstrate the data preparation, design, and implementation of cross-organizational PM for the use in IT DD and derive design principles to provide scholars and practitioners with design knowledge when implementing PM in this setting. In this light, we also point toward challenges that might emerge when applying cross-organizational PM in a particularly sensitive setting such as IT DD, where the information asymmetry between buyer and target is considered not only an obstacle but also an advantage (Boeh, 2011). To this end, our study gives first indications on how to address these challenges, for example, through establishing the contractual basis for sharing sensitive process data and anonymizing data when possible, which might be helpful in other sensitive cross-organizational contexts where organizations could learn from each other while preserving critical private information, such as in public administration or health. We, therefore, encourage scholars to build on our findings and further study technical and sociotechnical measures to facilitate cross-organizational PM.

Consequently, our research provides practitioners with a systematic understanding of how to approach process assessment in the context of IT DD by giving an overview of dimensions to consider and corresponding indicators to measure when assessing the target's (and potentially also the buyer's) processes in the pre-deal phase of an M&A transaction. Our framework of operationalized process assessment dimensions gives practitioners the flexibility to focus the process assessment on particular dimensions of interest depending on the context of the M&A transaction, for example, focusing on process standardization and conformance to regulations in the highly regulated fields of banking or pharmaceutical. In addition, we provide practitioners with design knowledge and a prototypical PM artifact to support the process assessment in IT DD with PM as a data-driven and, compared to the traditional approaches of interviews and the analysis of documentation, efficient approach to creating process transparency.

We acknowledge that our research is subject to several limitations that open up avenues for future research. First, even though we grounded the analysis of requirements and operationalization of indicators for process assessment in IT DD in related literature and practice, the topic of process assessment only recently came into the focus of IT DD. Thus, additional requirements and indicators might emerge with time as process assessment becomes an integral part of IT DD in practice, which we encourage scholars to account for by collecting empirical data in the field on process assessment in the context of IT DD. Second, even though we demonstrated the applicability of PM to support the process assessment in the context of IT DD based on real process data, the demonstration was focused on only two processes from firms in the (mechanical) engineering industry. While practice shows that assessing IT-enabled processes in IT DD plays an important role in the success of M&A transactions in digitally transforming industries (Zillmann, 2021), such as engineering, the assessment might require a different approach and yield different results in less digitalized industries. In addition, while the O2C and P2P processes chosen for demonstration are core processes of value creation at every firm, other processes might be relevant for assessment during the IT DD, depending on the target’s and buyer’s industries and products and the transactional goals. Thus, we consider it worthwhile for future research to investigate and derive insights from the application of PM in the context of M&A transactions in heterogeneous industries and heterogeneous processes to expand the applicability of our results. Finally, our results lay the foundation for the use of PM in the context of IT DD by operationalizing and demonstrating its applicability to evaluating IT-enabled processes at the buyer and the target and analyzing their conformance. Developing further comparative measures or forecasts was beyond the scope of our research but could be a valuable avenue for future research.

Conclusion

Driven by the digital transformation of organizations, in the context of M&A, assessing a target's IT-enabled business processes is becoming an increasingly important factor for buyers to consider during IT DD. However, research and practice lack knowledge on operationalizing and conducting this assessment. Addressing this challenge, our study synthesizes and operationalizes the requirements for process assessment in the context of IT DD, demonstrates the applicability of PM to conduct the process assessment, and provides design knowledge to guide the design, implementation, and use of PM for process assessment in the context of IT DD. We hope that the findings of our study serve as a starting point for scholars and practitioners alike to develop a deeper understanding of process assessment in the context of IT DD and to explore the possibilities of PM as a novel technological approach to support IT DD.

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