# Managing Dynamic Business Processes
## A Process Mining Perspective on Workarounds and Knowledge-Intensive Processes

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| **Dekan** | Prof. Dr. Jens Müller |
| **Gutachter** | Prof. Dr. Daniel Beverungen<br>Prof. Dr. Ralf Plattfaut |
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# Foreword

*The art of progress is to preserve order amid change, and to preserve change amid order, wrote Alfred North Whitehead—one of the leading philosophers of process and change.* His observation captures a central challenge of Business Process Management: Organizations need stable processes to create value efficiently and reliably, while remaining able to respond to unforeseen circumstances and dynamic environments.

In this spirit, Bernd Löhr's doctoral thesis explores how business processes can be analyzed and dynamically shaped through innovative models, methods, and software tools. Bernd advances process mining beyond standardized, frequently repeated processes by developing new approaches for knowledge-intensive processes in which expertise, judgment, and adaptation play decisive roles. His dissertation also offers a differentiated perspective on workarounds. Rather than treating workarounds merely as undesirable deviations, Bernd examines how they can be found in event data, how they should be interpreted, and how valuable workarounds can be transformed into process innovations at the organizational level. In this way, workarounds become sources of organizational learning and innovation rather than remaining deviations that organizations strive to eliminate.

Conceptually and technically, Bernd's work demonstrates how processes can be both efficient in day-to-day operations and open to innovation and transformation. To ensure that his results address pressing needs of companies, he conducted his research in the BPMI 4.0 project with Weidmüller and GEA, and in the ChangeWorkAROUND project with viadee, myConsult, REMBE, UNITY, and Westfalen. Bernd approached these collaborations with a genuine interest in practitioners' challenges and a strong commitment to developing solutions that are both scientifically rigorous and practically useful.

When Bernd joined our research group, he was already an excellent software developer with a strong interest in designing innovative IT artifacts. Over the years, I had the pleasure of seeing him develop into an accomplished researcher who combines outstanding technical abilities with theoretical rigor and methodological care—a development that was, I admit, astonishing and pleasantly surprising to me. Bernd was also always eager to share his latest findings with our students, particularly in our Business Process Management courses. His dissertation marks the successful completion of his doctoral journey and the conclusion of many years of productive academic collaboration within our research group.

It is a pleasant coincidence that Bernd comes from Beverungen—a town with which, for obvious reasons, I feel a special connection. Perhaps his achievement can encourage others to see that a successful career can, quite literally, start from Beverungen. I trust that Bernd will make a fine career as a process manager in companies that fit his profile, perhaps a small or medium-sized company that is built on lasting values of responsibility, friendliness, an open-minded attitude, and respectful interactions. I wish him every success and am confident that he will successfully navigate the balance between order and change.

Paderborn, July 2026 Prof. Dr. Daniel Beverungen

# Acknowledgements

A dissertation like this is always a group effort, whether from a scientific or a social perspective. When I started this journey back in 2021, I assumed—but did not fully grasp—how taxing it would become for me and for the colleagues, friends, and family accompanying me.

First, I would like to thank Daniel, who gave me the chance to start this academic journey. You always supported me over the years, provided guidance, and offered a warm welcome when I arrived at the university. Without you and your passion for processes, I probably would never have walked this path. Thank you for shaping both my research and my thesis, for giving me the opportunity to travel, and for encouraging me to push myself.

In the same vein, I would like to thank Christian (my academic big brother), who talked me into this position and has been my mentor during most of my time here. If you had not asked me in 2019 to join Daniel's chair, I am not sure whether I would have pursued a PhD.

Moreover, my thanks go to my colleagues, who have become great friends: Kathi, Philipp (Hansi), Philipp (PzH), Caro, Malte, Agnes, Jannika, Johann, Lennart, Talea, Luc, Simon, Jenni, Sascha, Birgit, and Alex. Thank you for the great discussions, events, and conference journeys. I always loved rambling about our work, sharing weird stories about our students, or just talking about a good game or movie. Creating this dissertation—and all the papers included in it—would not have been possible without you.

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Finally, a big part of this journey was my family: Roswitha, Alfred, and Adrian. Thank you for giving me the room to grow and to take on this endeavor. Without your love and support, I probably would never have started studying and pursued this journey.

My biggest thanks go to my better half, Jacky. You have accompanied me for so many years—since we were at school—through my studies, the PhD, and hopefully for many more years to come. You listened to my problems, made me laugh, hugged and cuddled me, showed me how awesome (and stubborn) ponies can be, and so much more. You supported me during my PhD while we were renovating our house at the same time. Thank you for everything! I love you!

Paderborn, July 2026 Bernd Löhr

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# Part A
# Research Overview

# 1 Introduction

## 1.1 Background and Motivation

Processes play a fundamental role in every organization, whether their presence is consciously acknowledged or not (Dumas et al., 2018). Since the 1990s, business process management (BPM) has frequently promoted the notion that "*everything is a process*", a mantra that perfectly captures how processes can range from small manual tasks to large-scale strategic initiatives (Fettke and Di Francescomarino, 2025). Although processes have often been conceptualized as structurally stable entities, they continuously evolve as the environments in which they operate become increasingly volatile (Röglinger et al., 2022; Grisold, Janiesch, et al., 2024; vom Brocke et al., 2024). Understanding, capturing, and managing these dynamics—while leveraging human creativity to respond to novel situations—remains a crucial yet challenging endeavor that warrants further scholarly attention.

Early research demonstrated that well-managed processes can provide organizations with a significant competitive advantage (Davenport, 1993). At the same time, a process perspective has long emphasized flow and transformation rather than static states (Rescher, 1996). Nevertheless, both research and practice tended for many years to treat processes as stable structures optimized for efficiency and predictability (vom Brocke et al., 2024; Rosemann et al., 2024). As environments, technologies, and organizational arrangements have evolved, however, the intensity and visibility of process change have increased substantially (Röglinger et al., 2022).

In practice, organizational processes change in manifold ways. These changes may be intentional or unintentional, incremental or radical, and stem from diverse causes (König et al., 2019). Exogenous shocks—such as the COVID-19 pandemic, global trade conflicts, or military crises—can disrupt established processes profoundly (Röglinger et al., 2022). Likewise, endogenous changes (Andrews, Suriadi, Wynn, et al., 2018), including shifts in roles, resources, or localized work practices, can reshape process flows partially or entirely (Bartelheimer et al., 2023; Pentland, Liu, et al., 2020). Process dynamics thus emerge from the continuous interaction between organizations and their technological, political, and market environments.

In this sense, process dynamics describe the evolution of a process's structure and execution patterns over time, driven by technological innovation, expanding data capabilities, and the ongoing adjustments of organizational actors, as emphasized in routine dynamics research (Feldman and Pentland, 2003; Wurm et al., 2021; Grisold, Janiesch, et al., 2024). These developments challenge traditional BPM assumptions grounded in stability, predictability, and efficiency (Rosemann et al., 2024). Digital transformation has introduced heightened variability, complexity, and temporal pressure, necessitating new theoretical and practical approaches to understand how and why processes evolve during execution (vom Brocke et al., 2014; Rosemann et al., 2008; Recker et al., 2009; Baiyere et al., 2020; Beverungen et al., 2021; Grisold et al., 2022; Röglinger et al., 2022). Emerging technologies such as artificial intelligence (AI) (Rosemann et al., 2024), robotic process automation (RPA) (Syed, Suriadi, et al., 2020), and process mining (van der Aalst, 2016) further amplify these dynamics by enabling flexible, granular, and near real-time insights into how processes unfold and change (Leonardi and Treem, 2020; vom Brocke et al., 2024).

Process dynamics and related concepts (see Section 2.1.2) encompass continuous change across different levels of abstraction and varying perspectives (Grisold, Janiesch, et al., 2024). For instance, process flexibility as part of BPM research focuses on the adaptability of processes (Schonenberg et al., 2008), while routine dynamics as part of organization science emphasize variability in execution over time (Feldman et al., 2021). The focal change can range from large-scale transformations, such as shifts in a process's strategic orientation (Davenport, 1993), to small-scale adaptations, such as using an alternative yet effective tool when performing a routine task (Alter, 2014; Beerepoot et al., 2019). From a process management or upper-management perspective, such deviations are often unintended—particularly in high-volume, highly standardized processes, such as an order-to-cash process at a large online retailer like Amazon (Carmona et al., 2022).

An additional type dynamic processes are knowledge-intensive processes (KIPs), such as product development processes. They inherently require substantial amounts of knowledge, judgment, and creativity and are also strategically relevant for retaining a competitive advantage (Di Ciccio et al., 2015). Prescribing in detail how process participants should perform their work can constrain the creative potential of such processes. Instead, KIPs are typically organized in a semi-structured manner or in stages, in which specific criteria must be fulfilled while the means to achieve them remain unspecified (R. G. Cooper, 1990). Within the boundaries of each stage, control flows and relevant activities emerge (Marjanovic, 2005), driven by the agency of participants (Leonardi, 2011) as well as contextual requirements (Andrews, Suriadi, Wynn, et al., 2018; Röglinger et al., 2022). In such settings, these processes represent a form of top-down intended dynamic behavior, which is congruent with concepts such as flexibility-by-design (Schonenberg et al., 2008) or light touch processes (Baiyere et al., 2020). Both describe processes whose models are intentionally flexible to allow process participants to work as they see fit. However, this self-imposed flexibility and the resulting variance lead to isolated knowledge tied to individual knowledge bearers, which in turn leads to inefficiencies such as repeated mistakes (Ramesh and Tiwana, 1999; Isik et al., 2012).

Beyond these larger-scale and often intentional forms of dynamism, processes are also shaped by smaller, bottom-up phenomena. In both knowledge-intensive processes (KIPs) and highly standardized processes, participants frequently deviate from intended to-be processes for various reasons (Beverungen, 2014). Goal-directed deviations aimed at accomplishing work and maintaining process performance are commonly referred to as workarounds (Alter, 2014). Such deviations are typically triggered by underlying misfits that hinder smooth process execution. These misfits may arise from inadequate information systems, under-specified or contradictory process designs, organizational constraints, insufficient training, or newly emerging exogenous requirements (Bartelheimer et al., 2023). Overcoming them often requires ingenuity and may lead to minor, localized adjustments or, in some cases, to strategic changes that fundamentally reshape organizational processes or even business models. In process modeling, concepts such as flexibility-by-deviation acknowledge the necessity of dynamically responding to obstacles and moving beyond the prescribed process model (Schonenberg et al., 2008). Prior research demonstrates that workarounds can foster bottom-up process innovation, either by offering superior solutions or by revealing deeper structural issues (Beerepoot and Van de Weerd, 2018). At the same time, managing workarounds remains challenging. They frequently go unnoticed or are insufficiently addressed, potentially triggering cascading effects across the organization (Leonardi, 2011). Addressing these challenges requires a combination of qualitative, quantitative, and mixed-method approaches.

One prominent quantitative approach to supporting BPM in increasingly dynamic environments is process mining. Process mining bridges the gap between data science and BPM by leveraging the digital traces left behind in information systems to analyze how processes are actually executed (IEEE Task Force on Process Mining, 2012; van der Aalst, 2022). Since its early conceptualization in the early 2000s (van der Aalst et al., 2003), process mining has evolved into a mature discipline and a widely adopted set of techniques that support organizations in understanding, monitoring, and improving their processes (van der Aalst, 2022). This development is also reflected in practice, where software vendors such as Celonis or Signavio have experienced rapid growth, with process mining tools becoming an integral component of digital transformation initiatives across industries (Deloitte, 2025).

At its core, process mining promises to increase transparency regarding the *as-is* execution and performance of processes, thereby providing a data-driven foundation for informed interventions (IEEE Task Force on Process Mining, 2012). Contemporary process mining techniques span multiple categories, including process discovery, conformance checking, performance analysis, comparative process mining, predictive process mining, and action-oriented process mining (van der Aalst, 2022). These techniques enable analysts not only to detect bottlenecks, deviations, and inefficiencies retrospectively, but increasingly also to support the improvement of running process instances in near real time (van der Aalst, 2022). As a result, process mining has become an important enabler for organizations seeking to manage processes in a more structured, evidence-based manner and has gained traction across a wide range of application domains (Deloitte, 2025).

Beyond efficiency-oriented improvements, process mining is particularly promising in contexts characterized by high variability and dynamics (Pentland et al., 2021). KIPs, for example, are often managed manually or receive only limited IT support from a BPM perspective (Di Ciccio et al., 2015). As a consequence, errors and suboptimal practices tend to be repeated over time (Ramesh and Tiwana, 1999), while learning remains largely implicit. By making execution patterns visible, process mining can contribute to a more systematic understanding of KIPs, supporting both process improvement and organizational knowledge creation (Nonaka and Takeuchi, 1995). In doing so, it offers a quantitative lens on how process dynamics emerge from the situated actions of knowledgeable actors.

Similarly, a process mining perspective enables a more systematic investigation of unintended dynamic behavior such as workarounds (Outmazgin et al., 2023). These often remain hidden from formal process models and managerial oversight, especially when qualitative approaches are infeasible or incomplete (Alter, 2014). Analyzing event data allows researchers and practitioners to identify how workarounds manifest in process executions and how they affect overall process behavior (van der Waal, van de Weerd, et al., 2024). Making workarounds observable and measurable provides a foundation for their active management, supporting informed decisions on whether to prevent, adopt, adapt, or deliberately ignore specific practices (Beerepoot and Van de Weerd, 2018). In this sense, process mining does not merely document deviations from intended processes but offers a powerful means to understand and govern process dynamics that emerge during execution.

## 1.2 Research Problem and Research Objectives

As shown, business processes are inherently dynamic, and both top-down intended flexibility, as found in knowledge-intensive processes (Di Ciccio et al., 2015), as well as bottom-up emergent behavior, such as workarounds (Alter, 2014), are central sources of continuous process change (vom Brocke et al., 2024). Process mining constitutes a powerful quantitative approach for making process executions visible (van der Aalst, 2022) and for supporting evidence-based process management in such dynamic settings. Despite this apparent fit between problem and solution, the application of process mining in dynamic and knowledge-intensive contexts remains challenging in practice and theory alike.

Empirical evidence suggests that many organizations struggle to successfully apply process mining beyond well-structured, high-volume processes (Martin et al., 2021; Kerpedzhiev et al., 2021). A key reason for this struggle lies in the dominant orientation of existing research. Much of the process mining literature focuses on the conceptual and artificial development of algorithms and IT artifacts, frequently adapting techniques from the data science domain to BPM-related problems (Mehdiyev and Fettke, 2020; Senderovich et al., 2015; van der Aalst, 2016). As noted by vom Brocke et al., 2021a, (p. 483), *"research on process mining has mostly focused on devising new or better algorithms."* While these contributions are indispensable for advancing the technical state of the art, they offer limited guidance on how process mining can be effectively employed in organizational settings characterized by emergence, heterogeneity, and ongoing change (vom Brocke et al., 2024).

These limitations become particularly pronounced when process mining is applied to knowledge-intensive processes and workarounds. Process mining techniques rely fundamentally on the availability of high-quality event logs to generate meaningful insights (Buijs et al., 2014). However, in dynamic settings, event data is often incomplete, ambiguous, or misaligned with actual work practices (Bose et al., 2013). Process dynamics frequently lead to mismatches between prescribed process models and observed execution data (Rogge-Solti et al., 2016), or to event logs of insufficient quality (Rogge-Solti et al., 2013). In the case of KIPs, this challenge is amplified, as traditional event logs typically fail to capture the relevant knowledge-related aspects of work (Di Ciccio et al., 2015).

Workarounds further complicate the situation. Although they are widely recognized as a pervasive and potentially innovative form of bottom-up process change, workarounds often remain weakly represented—or entirely invisible—in process data, making a better understanding of their data implications necessary. Their identification presupposes truthful and trustworthy event logs (van der Waal, van de Weerd, et al., 2024; Carmona et al., 2022), yet this assumption is problematic precisely because workarounds may involve bypassing, repurposing, or selectively using information systems (Alter, 2014).

Workarounds may occur in all kinds of business processes (Alter, 2014), potentially affecting the organization as a whole, while KIPs are frequently of strategic importance for organizations (Di Ciccio et al., 2015; Ramesh and Tiwana, 1999). Despite their relevance to organizational success, KIPs and workarounds tend to receive limited attention from data-driven BPM approaches. Additionally, systematic management concepts for dealing with workarounds are only beginning to emerge (Bartelheimer et al., 2023). Consequently, while process mining is increasingly promoted as a means to cope with complexity and change, there is still insufficient understanding of how it can be adapted to account for dynamic behavior, imperfect data, and the situated actions of knowledgeable actors.

Taken together, these observations reveal a fundamental gap between the theoretical potential of process mining and its practical applicability to dynamic processes. Addressing this gap requires moving beyond algorithm-centric perspectives toward a more nuanced understanding of how process mining can be applied under conditions of continuous change as well as data imperfections. This leads to the following research problem:

**Research Problem.** *Comprehensive knowledge on how to establish process mining for intentionally dynamic processes, such as knowledge-intensive processes, and for dynamic behavior such as workarounds, is missing. Particularly, approaches for managing the dynamic nature of such processes remain underexplored.*

To address this problem, this thesis establishes four research objectives, which aim to pave the way for generating applicable knowledge on leveraging process mining for dynamic processes. However, before examining knowledge-intensive processes and workarounds in detail, it is first necessary to further investigate the organizational competencies required to successfully leverage process mining to better understand the increasingly dynamic contexts, including the dynamics process mining itself introduces. Then, as part of the second objective, the focus moves onto the actual application of process mining by designing a process mining tool for knowledge-intensive processes. For the third research objective, we shift towards workarounds and systematize how they can be identified and analyzed using process mining. Finally, the focus moves beyond process mining and towards the design of structured approaches for managing and evaluating workarounds.

The growing complexity and interconnectedness of digitalized environments (Baiyere et al., 2020; Kerpedzhiev et al., 2021; Beverungen et al., 2021) challenge the foundational assumption that processes can be shaped top-down and revised periodically (vom Brocke et al., 2014; Rosemann et al., 2008; Recker et al., 2009). Simultaneously, technologies such as AI (Janiesch et al., 2021), robotic process automation (Syed, Suriadi, et al., 2020), and particularly process mining (van der Aalst, 2016) create new opportunities to improve processes. By leveraging event data from operational systems, process mining enables unprecedented transparency, real-time insights, and responsiveness in BPM (van der Aalst, 2016; IEEE Task Force on Process Mining, 2012; Galic and Wolf, 2021; Grisold et al., 2020), fundamentally enhancing the discipline's capacity to manage dynamic and complex process landscapes (Grisold et al., 2022; Kipping et al., 2022).

Despite these promises, organizations frequently struggle to translate the potential of process mining into sustained value creation. Although a majority of companies express interest or have initiated initial projects, widespread adoption remains limited (Forrester Research Inc., 2022). Even organizations already employing process mining face challenges such as insufficient management support and data-related barriers (Martin et al., 2021). Research on value creation through process mining is still nascent (Badakhshan et al., 2022), and practical guidance often lacks rigorous grounding (Reinkemeyer, 2020b; Linden, 2021; Reinkemeyer et al., 2022). These shortcomings have triggered calls for deeper inquiries into how BPM can effectively integrate data-driven technologies, including the development of specific maturity models (Dunzer et al., 2021; Martin et al., 2021; Beverungen et al., 2021). Addressing this gap requires a clearer understanding of what organizations must be capable of to realize the promised benefits of process mining. Thus, the objective of this research is **[Research Objective 1]** *to systematize the required competencies in organizations for creating value with process mining*, laying the conceptual foundation for more mature, effective, and sustainable process mining initiatives.

KIPs (Di Ciccio et al., 2015), such as research and development or product innovation (Eppler et al., 1999), constitute a strategic cornerstone of modern organizations (de Almeida Rodrigues Gonçalves et al., 2023) because they enable firms to leverage specialized knowledge for competitive advantage (Nevo and Chan, 2007; Nonaka and von Krogh, 2009; Rai, 2011; Alavi and Leidner, 2001; Holsapple and Joshi, 2000; Mahapatra and Sarkar, 2000). Yet, KIPs differ profoundly from operational business processes: they are fluid, weakly structured, and heavily shaped by the tacit knowledge, creativity, and judgment of individuals (Di Ciccio et al., 2015; Isik et al., 2012; Eppler et al., 1999; Gronau and Weber, 2004). As a result, they lack high levels of standardization and instead represent a flexibility-by-design approach (Schonenberg et al., 2008) similar to light-touch processes (Baiyere et al., 2020). Consequently, system support that has enabled technologies such as process mining or AI agents to thrive in operational domains (Aureli et al., 2019) is limited in the context of KIPs. Furthermore, KIPs rely on fragmented process-related knowledge—much of it tacit and dispersed across departments, communities of practice, or the intuitions of individual experts (Ramesh and Tiwana, 1999). This fragmentation not only limits organizational learning but also increases the risk of repeated mistakes and knowledge loss, particularly when experienced employees leave. Consequently, organizations face substantial challenges in rendering the knowledge embedded in KIPs accessible, systematic, and reusable, even though doing so is vital for enabling rapid problem solving, effective knowledge transfer, and continuous innovation (Bruhin et al., 2025; Davenport and Prusak, 1998).

Process mining has proven powerful for understanding and improving operational processes (IEEE Task Force on Process Mining, 2012; van der Aalst and Carmona, 2022), but its current methods fall short when applied to KIPs. The reasons are threefold. First, process mining relies on explicit event data (van der Aalst, 2016; van der Aalst and Carmona, 2022), whereas KIPs rely predominantly on tacit knowledge that remains invisible in event logs (Marjanovic and Freeze, 2011; Di Ciccio et al., 2015; Ramesh and Tiwana, 1999) and is typically exchanged through social interaction (Nonaka and Takeuchi, 1995). Second, process mining assumes predefined models and structured workflows (van der Aalst, 2016; van der Aalst and Carmona, 2022), whereas KIPs often lack such models and derive value precisely from context-specific deviations (Di Ciccio et al., 2015; Eppler et al., 1999; Isik et al., 2012; Gronau and Weber, 2004). Third, current process mining techniques primarily optimize retrospective analysis, while KIPs require the real-time mobilization of process-related knowledge to guide ongoing work (Di Ciccio et al., 2015; Isik et al., 2012; Eppler et al., 1999; Gronau and Weber, 2004; de Almeida Rodrigues Gonçalves et al., 2023). These challenges highlight a crucial gap: organizations lack technological support to surface, share, and activate knowledge embedded in KIPs while these processes are unfolding. Addressing this gap requires rethinking how process mining can be designed to enable knowledge exchange, support decision-making, and bring to the forefront the tacit and experiential knowledge that drives KIPs. Therefore, the objective of this research is to **[Research Objective 2]** *design a process mining tool to support the management of knowledge-intensive processes by promoting the mobilization of process-related knowledge*.

While most organizations report substantial value from process mining—particularly in terms of transparency, throughput time reduction, and process improvement (Deloitte, 2023)—the utility of such analyses depends fundamentally on the accuracy and timeliness of the underlying event data. In practice, however, process data often fails to fully represent real-world execution: organizations frequently update event data infrequently (Deloitte, 2023), process models are updated only sporadically (Dumas et al., 2018), and event logs may be noisy or incomplete (Rogge-Solti et al., 2013). These shortcomings create mismatches between conceptual models, event logs, and actual process behavior (Rogge-Solti et al., 2016; Buijs et al., 2014), thereby weakening the reliability of conformance checking and related analyses. Importantly, even under ideal conditions—accurate logs and up-to-date process models—mismatches persist because process participants can always "*do otherwise*" (Giddens, 1984) by deviating from prescribed activities, circumventing systems, or appropriating them in unintended ways (Pentland and Feldman, 2005; Beverungen, 2014).

A consequential form of such deviations is a workaround (Alter, 2014; Bartelheimer et al., 2023; Soffer et al., 2023). They are increasingly recognized as a source of employee-induced process drift and dynamics (Grisold et al., 2020; Pentland et al., 2021; Bartelheimer et al., 2023), and thus represent a distinct lens through which mismatches between event data and real-world process execution can be understood. Yet, although persistent mismatches suggest the presence of workarounds, the BPM and process mining literature has not systematically examined how workarounds manifest in event data, nor how they can be reliably identified and analyzed. Existing approaches—including qualitative techniques (Beerepoot and Van de Weerd, 2018) and data-driven methods such as deep learning (Weinzierl et al., 2021) or the **S**emi-automated **WOR**karound **D**etection (**SWORD**) technique (van der Waal, van de Weerd, et al., 2024)—either require extensive prior knowledge, significant manual effort, or have been validated only in restricted domains such as healthcare or public administration. Given the growing importance of understanding employee-driven deviations and their role in shaping process dynamics, a systematic foundation is needed for detecting, interpreting, and analyzing workarounds across organizational contexts. Against this backdrop, the objective of this research is **[Research Objective 3]** *to systematize how workarounds manifest in process data and to identify them with data-driven means*.

Organizations must continuously innovate their processes to remain competitive in environments shaped by volatility, shifting customer expectations, and rapidly evolving market conditions. Within the BPM discipline, process innovation is broadly understood as the development and implementation of new or enhanced processes, methods, or systems that improve efficiency, effectiveness, and value creation (Dumas et al., 2018; de Oslo, 2018; vom Brocke and Schmiedel, 2015). While established approaches such as business process re-engineering and process redesign offer top-down mechanisms for enacting change (Dumas et al., 2018), organizations increasingly rely on more flexible forms of innovation that emerge bottom-up. Employee-centered process innovations—incremental, situated adaptations implemented autonomously by process participants—represent a vital but understudied source of organizational improvement (Dumas et al., 2018). Workarounds have been identified as a key mechanism underlying such bottom-up innovations (Bartelheimer et al., 2023) and reflect the creativity of employees as potential solutions (Röglinger et al., 2022). Although workarounds can catalyze creativity, increased customer satisfaction, and process improvements (Alter, 2015), they may also generate negative consequences such as compliance violations, quality issues, or process fragmentation (Alojairi, 2017; Pinto et al., 2018). This dual nature highlights the need for organizations to manage workarounds systematically rather than treating them merely as temporary fixes (Alter, 2014; Laumer et al., 2017).

Despite their potential, workarounds remain difficult to detect, evaluate, and translate into organization-wide improvements. Because workarounds are embedded in day-to-day routines and often diffuse informally through observation and communication (Bartelheimer et al., 2023), organizations struggle to recognize them as opportunities for structured innovation. Multiple barriers—cultural resistance, fear of repercussions, and the complexity of modern work environments—further obscure their identification (Bartelheimer et al., 2023). As a result, valuable bottom-up insights frequently fail to inform formal BPM activities, leaving a gap between individual ingenuity and organizational learning. Recent empirical work demonstrates that workarounds can indeed trigger organization-level process change (Bartelheimer et al., 2023) when supported by deliberate managerial attention and appropriate protocols, but current research offers limited guidance on the technological means required to support this transition. Given the growing importance of dynamic, responsive forms of process innovation—especially in environments where traditional business process re-engineering and redesign approaches prove too slow or rigid—there is a pressing need for IT support that enables organizations to systematically surface, assess, and leverage workarounds. Therefore, the objective of this research is to **[Research Objective 4]** *design approaches for managing and evaluating workarounds to foster bottom-up process innovations.*

## 1.3 Structure of the Dissertation

The identified research problem and the four resulting research objectives are examined in nine separate research articles. To elaborate on the connection between these research articles and their relevance to the IS research domain, the dissertation is structured into two parts: Part A and Part B.

In Part A, the research is elaborated and reflected upon in the context of the business process management discipline by focusing on the relevance of dynamic business processes and how process mining can be leveraged while managing them. The

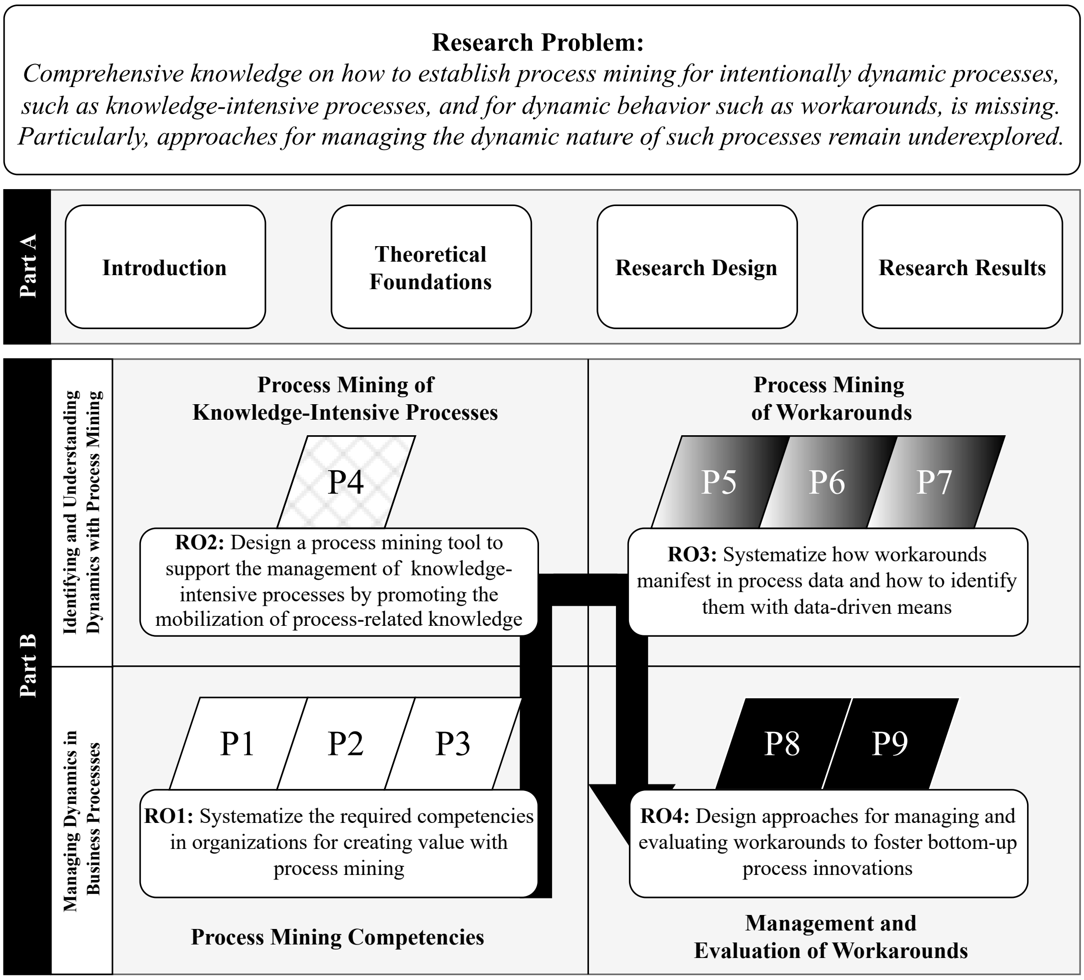


**Figure 1.1:** Structure of the Dissertation

remainder of this thesis is structured as follows: In Section 2, the theoretical foundations of business process management and dynamic processes—with a particular focus on KIPs and workarounds—are explored, while process mining and its respective applications to these processes are explained. This section is closed with the discussion of the current Process Science approach. In Section 3, the research design is presented by elaborating on the underlying research paradigms—namely Design Science Research—and the constituting research methods of this multi-methodological research approach. This primarily includes DSR-related methods as well as case studies, but also systematic literature reviews, whose specific interplay will be explained in detail. Section 4 summarizes the key findings from the research articles, addressing the research objectives and synthesizing the results. It highlights the theoretical and managerial contributions of the study and concludes by outlining its limitations and suggesting avenues for future research.

Part B consists of nine publications that have been published or are currently being considered for publication—i.e., under review—in peer-reviewed IS journals and conference proceedings. Figure 1.1 depicts each research article in relation to the identified research objectives. Relevant publishing outlets include the journals *Business & Information Systems Engineering (BISE)* and *Journal of Strategic Information Systems (JSIS)*. Conference proceedings include the *International Conference on Information Systems (ICIS)*, *European Conference on Information Systems (ECIS)*, *Americas Conference on Information Systems (AMCIS)*, and *International Conference on Business Process Management (BPM)*, including both the main conference and its workshops.

Part B is organized into four sections aligned with the identified research objectives. Figure 1.1 illustrates the overall structure of the dissertation and shows how the four research objectives are addressed by the included research articles, while Table 1.1 provides an overview of their metadata.

**Table 1.1:** Overview of Publications included in this Thesis

| #P | Author & Title | Outlet | JQ4 | CORE 2023 | Type | Status |
|---|---|---|---|---|---|---|
| | **Research Objective 1** | | | | | |
| **P1** | Brock, J., Brennig, K., Löhr, B., Bartelheimer, C., von Enzberg, S. & Dumitrescu, R. (2024). *Improving Process Mining Maturity – From Intentions to Actions.* | Business & Information Systems Engineering | B | / | J | P |
| | Pre-version of the journal publication:[1] | | | | | |
| | Brock, J., Löhr, B., Brennig, K., Seger, T., Bartelheimer, C., von Enzberg, S., Kühn, A., & Dumitrescu, R. (2023). *A Process Mining Maturity Model: Enabling Organizations to assess and improve their Process Mining Activities.* | European Conference on Information Systems | A | / | C | P |
| **P2** | Brennig, K., Löhr, B., Brock, J., Reineke, M., & Bartelheimer, C. (2024). *Maximizing the Impact of Process Mining Research: Four Strategic Guidelines.* | Americas' Conference on Information Systems | C | / | C | P |
| **P3** | Skolik, A. & Löhr, B. (2026). *Understanding the Dynamics of a Process Mining Project - Analyzing Log Data of a Process Mining Platform.* | Business Process Management Workshops | C | / | C | P |
| | **Research Objective 2** | | | | | |
| **P4** | Brennig, K., Bartelheimer, C., Löhr, B., Beverungen, D. & Müller, O. (2026). *Design Principles for Process Mining of Knowledge-Intensive Processes: An Action Design Research Study.* *Currently in the second revision phase* | Journal of Strategic Information Systems | A | / | J | U |
| | Pre-version of the journal publication:[2] | | | | | |
| | Löhr, B., Brennig, K., Bartelheimer, C., Beverungen, D. & Müller, O. (2022). *Process Mining of Knowledge- Intensive Processes: An Action Design Research Study in Manufacturing.* | International Conference on Business Process Management | B | A | C | P |
| | **Research Objective 3** | | | | | |
| **P5** | Löhr, B., Bartelheimer, C., Köhne, F., Nordlohne, F., Alile, D. & Latten, A. (2025). *Forging the LongSWORD: Exaptation and Enhancement of the SWORD Framework for Workaround Detection.* | Business Process Management Workshops | C | / | C | P |
| **P6** | Löhr, B. (2026). *Drafting the ChainSWORD – Towards Identifying Workaround Chains with Object-Centric Process Mining.* | European Conference on Information Systems | A | / | C | P |
| **P7** | Bartelheimer, C., Löhr, B., Reineke, M., Aßbrock, A. & Beverungen, D. (2025). *Workarounds as a Cause of Mismatches in Business Processes - Insights from a Multiple Case Study.* | Business & Information Systems Engineering | B | / | J | P |
| | **Research Objective 4** | | | | | |
| **P8** | Aßbrock, A., Löhr, B., Bartelheimer, C., & Beverungen, D. (2024). *Workarounds as Catalysts for Process Innovation: A Multiple Case Study on Pitfalls and Protocols.* | International Conference on Information Systems | A | / | C | P |
| **P9** | Reineke, M., Löhr, B., Aßbrock, A., Bartelheimer, C. & Beverungen, D. (2026). *From Temporary Fixes to Informed Decisions—Design Echelons for Evaluating Workarounds.* | International Conference on Business Process Management | B | A | C | P |

*Type:* C: Conference Paper, J: Journal Paper

*Status:* P: Published, U: Under Review

[1] This paper is not included in Part B of the thesis, as its results are already incorporated into the corresponding journal publication. Apart from minor refinements to the definitions of the 23 elements—made in response to reviewer feedback—no substantive changes have been introduced.
[2] This paper is not included in Part B of the thesis, as its results are already incorporated into the corresponding journal publication. This paper reports on an intermediate artifact reflecting the first half of the corresponding research project. P4 then reports on the final artifact with relevant changes to the artifact and the design principles.

# 2 Theoretical Foundations

## 2.1 A Dynamics Perspective on Business Process Management

### 2.1.1 Foundations of Business Process Management

Business process management (BPM) has emerged as a central discipline for managing and improving organizational work in increasingly dynamic and digital environments. Trends such as digitalization, globalization, big data analytics, and real-time computing have transformed organizational processes into complex and continuously evolving chains of events (van der Aalst, 2016; Beverungen et al., 2021). To cope with this complexity, organizations require systematic methods and tools that increase process transparency, control, and efficiency (Beverungen et al., 2021). BPM addresses this need by providing a structured set of methods, techniques, and tools for the process-based management of work (Dumas et al., 2018). It is commonly defined as *"the art and science of overseeing how work is performed in an organization to ensure consistent outcomes and to take advantage of improvement opportunities"* (Dumas et al., 2018, p. 1). Complementing this view, BPM has been characterized as a boundary-spanning research field that integrates managerial, organizational, and technological perspectives on the (re-)design and continuous management of business processes across different contexts (Rosemann and vom Brocke, 2015).

Historically, BPM builds on earlier process-oriented approaches, most notably business process re-engineering (BPR), which emerged in the early 1990s. BPR advocated a fundamental rethinking and radical redesign of business processes to achieve dramatic improvements in performance (Hammer and Champy, 1993, p. 32). While BPR established process thinking as a core managerial paradigm, its emphasis on radical, one-off change led to the development of BPM as a more continuous and sustainable management discipline. BPM extends this foundation by focusing on incremental improvement, organizational learning, and the systematic use of information technology to support ongoing process change (Dumas et al., 2018).

A central concept of BPM is the BPM lifecycle, which provides a structured framework for the continuous management and improvement of business processes. The lifecycle consists of six iterative phases: *process identification*, *discovery*, *analysis*, *redesign*, *implementation*, and *monitoring and controlling* (Dumas et al., 2018). It guides organizations in aligning business processes with strategic objectives while accounting for performance indicators, customer expectations, and contextual constraints (van der Aalst, 2016). Prior research emphasizes that BPM initiatives must be tailored to their organizational context, as one-size-fits-all approaches are prone to failure (vom Brocke et al., 2016, p. 486). Given the strong link between process quality and operational performance, continuous process management and improvement are regarded as essential organizational capabilities (Dumas et al., 2018).

Within the BPM lifecycle, information technology plays a pivotal role as both an enabler and a constraint of process execution and change. In this context, process mining has gained prominence as a data-driven approach at the intersection of BPM and data science (van der Aalst, 2016). By analyzing event logs that capture the execution of process activities, process mining enables the discovery of actual process behavior, the detection of deviations, and the identification of improvement opportunities (van der Aalst, 2016; Beverungen et al., 2021). It further supports the monitoring and controlling of processes with retrospective analyses (van der Aalst, 2016) but also support for running processes is getting more sophisticated through approaches such as predictive process monitoring (Marquez-Chamorro et al., 2018) or action oriented process mining (Park and van der Aalst, 2022). As such, it complements traditional BPM methods and supports evidence-based process analysis and improvement across multiple lifecycle phases (see Section 2.2).

### 2.1.2 Continuous Change in Business Processes

Historically, BPM has often been associated with the imposition of stable and prescriptive process models that process participants were expected to follow (Rosemann et al., 2024). Deviations from these models were typically treated as unintended exceptions or even as failures of compliance (Carmona et al., 2022). This static view contrasts with empirical observations showing that process participants frequently deviate from prescribed procedures when situational demands, constraints, or goals require them to do so (Beverungen, 2014). Such deviations are not anomalies but constitute different forms of change unfolding during process execution.

As a result, the study of change over time in business processes has gained increasing attention within BPM and related disciplines, giving rise to a diverse set of concepts addressing dynamic behavior (Grisold, Janiesch, et al., 2024). What unites these perspectives is their emphasis on dynamics, understood as forces that produce movement or change within a system (Grisold, Janiesch, et al., 2024). Processes have been described as being in a state of constant drift (Beverungen, 2014), shaped by endogenous developments such as learning or local adaptation (Andrews, Suriadi, Wynn, et al., 2018), as well as exogenous events including regulatory changes or technological disruptions (Röglinger et al., 2022). These dynamics underpin phenomena such as process flexibility, process and concept drift, routine dynamics, emergent processes, and dynamic capabilities (Grisold, Janiesch, et al., 2024).

Table 2.1 summarizes the main conceptual lenses through which dynamics in and around business processes are theorized in the literature and positions them with regard to their understanding of change and their relevance for BPM and process mining. The various concepts will be explained the following:

Within BPM research, dynamics are most prominently associated with **process flexibility** and the continuous adaptation of process designs. This line of work highlights the persistent mismatch between designed (*to-be*) process models and their actual (*as-is*) enactments, which struggle to keep pace with organizational change (Dumas et al., 2018). A central assumption in this literature is that at least some forms of future change can be anticipated and addressed through design-time mechanisms. Approaches such as flexibility-by-design, flexibility-by-deviation, and flexibility-by-underspecification seek to enable controlled variation during execution while maintaining overall process coherence (Schonenberg et al., 2008). Related concepts include **light-touch processes**, which are structured to be modifiable rather than rigidly fixed (Baiyere et al., 2020). Accordingly, infrastructural flexibility is helpful in actively supporting dynamic processes (Baiyere et al., 2020). From this perspective, dynamics are treated as manageable and, to some extent, foreseeable phenomena that can be incorporated into modeling and monitoring practices (Grisold, Janiesch, et al., 2024).

**Table 2.1:** Conceptualizations of dynamics in business processes and related disciplines

| Concept | Research Community | View on Dynamics | Key Sources |
|---|---|---|---|
| **Process drift and concept drift** | Computer science / process mining | Dynamics are understood as observable changes in execution behavior over time. Changes manifest as evolving process variants, deviations, or shifts in control-flow, data usage, or resources. Research focuses on detecting and analyzing such changes in event logs. | (Bose et al., 2014; Suriadi et al., 2014; König et al., 2019; Röglinger et al., 2022) |
| **Process flexibility** | BPM / workflow research | Dynamics are anticipated and incorporated into process design through mechanisms such as flexibility-by-design, flexibility-by-deviation, and flexibility-by-underspecification. The aim is to enable controlled variation during execution while preserving overall process coherence. | (Schonenberg et al., 2008) |
| **Emergent processes** | BPM research | Processes cannot be fully predefined but evolve during execution as participants respond to novel situations and develop solutions through situated deliberation and knowledge sharing. | (Marjanovic, 2005) |
| **Light-touch processes** | BPM / digital transformation research | Processes are intentionally designed to remain modifiable rather than rigidly fixed. Rather than prescribing detailed execution paths, they provide minimal structure that allows actors to adapt process enactment to evolving contexts and opportunities. | (Baiyere et al., 2020) |
| **Process dynamics through drift** | Organization science / information systems | Processes evolve through continuous endogenous change as participants introduce small variations in action sequences. Over time, these incremental adjustments may accumulate and lead to bursts of complexity and structural phase changes in the process. | (Pentland, Liu, et al., 2020) |
| **Process drift through situated enactment** | BPM / socio-technical process research | Processes evolve through situated adaptations and improvisations by participants responding to contextual conditions, technologies, and emerging constraints. Such drift may accumulate incrementally and eventually produce new dominant patterns of action. | (Beverungen, 2014) |
| **Routine dynamics** | Organization science | Processes are conceptualized as organizational routines consisting of repetitive patterns of interdependent actions. Dynamics arise from the interplay between ostensive representations (e.g., process models) and performative enactments by actors. This interaction simultaneously produces stability and change. | (Feldman and Pentland, 2003; Feldman et al., 2019; Pentland et al., 2012; Wurm et al., 2021) |
| **Human and material agency in routines** | Sociomaterial research | Dynamics result from the ongoing imbrication of human intentions and material affordances. Technologies both enable and constrain actions, thereby shaping how routines evolve over time. | (Leonardi, 2011; Hutchby, 2001) |
| **Behavioral visibility** | Digital work and organizational transparency research | Digital infrastructures increase the visibility of actions and process traces, enabling reflection, comparison, and learning while also potentially constraining experimentation due to increased scrutiny. | (Leonardi and Treem, 2020; Feldman and Pentland, 2003) |
| **Dynamic capabilities** | Strategic management | Dynamics are framed as an organization's capability to sense environmental changes, seize opportunities, and transform resources and processes to maintain competitiveness in volatile environments. | (Teece et al., 1997; Pavlou and El Sawy, 2011) |

Under the notion of **process dynamics**, it is emphasized how processes evolve through situated enactment. The ongoing digital transformation introduces new information systems and forms of digital interaction that reshape work practices and prompt incremental adjustments by process participants (Pentland, Liu, et al., 2020). These adjustments often manifest as workarounds—locally developed practices that bypass or repurpose formal process arrangements (Alter, 2014). Digital technologies play an ambivalent role in this regard: they can enable new forms of coordination while simultaneously constraining action, thereby provoking adaptive responses (Beverungen, 2014). Simulation-based research suggests that drift can increase process complexity by expanding the number of viable execution paths until a critical tipping point is reached, after which new dominant paths emerge and restore relative stability through self-organizing dynamics (Pentland, Liu, et al., 2020). Whether such dynamics are desirable depends on the organizational context and industry characteristics.

In organization science, dynamics are most prominently discussed through the lens of routine dynamics and dynamic capabilities. **Routine dynamics** conceptualize processes as organizational routines—repetitive, recognizable patterns of interdependent action—that are continuously enacted and modified in practice (Feldman and Pentland, 2003; Feldman et al., 2019). Central to this perspective is the distinction between ostensive aspects, which capture abstract understandings of a routine, and performative aspects, which refer to situated enactments. Their interplay explains how routines remain recognizable while evolving over time (Feldman and Pentland, 2003; Pentland et al., 2012; Dittrich and Seidl, 2017). Unlike BPM's predominantly prescriptive orientation, routine dynamics adopts a descriptive and explanatory perspective on change (Wurm et al., 2021; Recker, 2014).

**Dynamic capabilities** research shifts the focus further to the organizational level, conceptualizing dynamics as an organization's capacity to sense, seize, and transform in response to environmental turbulence (Teece et al., 1997; Pavlou and El Sawy, 2011). From this perspective, future states are fundamentally uncertain and cannot be reliably extrapolated from past behavior. Dynamics are therefore not deviations from stability but an inherent condition of organizing in volatile environments (Grisold, Janiesch, et al., 2024).

A complementary perspective on dynamics foregrounds the role of agency in shaping process change. **Human agency** in routines and processes refers to actors' capacity to form intentions, pursue goals, and reflexively adapt their actions in situated work practices (Emirbayer and Mische, 1998). From this view, processes are not merely executed but continuously enacted, as actors interpret formal structures and adjust their behavior in response to local conditions. Leonardi (2011) conceptualizes human agency as goal-oriented action that unfolds within, and in relation to, existing routines and technologies, highlighting that processes are neither fully determined by formal models nor entirely discretionary. This ongoing enactment plays a central role in the emergence and stabilization of workarounds (Alter, 2014).

Human agency is closely intertwined with **material agency**, which denotes the capacity of technologies and artifacts to shape action in ways that are not fully reducible to human intention. Material agency manifests through the performative properties of technologies, such as system-enforced sequences, automated calculations, or predefined representations. To explain how process and routine dynamics emerge over time, Leonardi (2011) introduces the concept of imbrication, describing the sequential interweaving of human and material agency. Through repeated imbrications, routines and technologies are produced, stabilized, and transformed, allowing processes to exhibit both persistence and change. Material agency can be experienced as constraining when technological features limit actors' ability to pursue evolving goals, but it can also be enabling by affording novel possibilities for action that actors integrate into their routines (Leonardi, 2011; Hutchby, 2001; Feldman and Pentland, 2003). These limiting and enabling aspects are closely related to how IT artifacts enable and constrain processes and routines (Beverungen, 2014).

Digital technologies further intensify process dynamics by increasing **behavioral visibility**. Behavioral visibility refers to the extent to which the behaviors of individuals, collectives, or technologies become observable to third parties through digital infrastructures with minimal effort (Leonardi and Treem, 2020). Rather than relying on direct observation, visibility emerges through digitization, datafication, and algorithmic ordering, which render process execution as persistent and interpretable traces. Behavioral visibility reshapes process and routine dynamics by altering how actions are performed, evaluated, and adapted over time. Increased visibility can stabilize routines through standardization and accountability, but it can also provoke change by enabling comparison, reflection, and learning (Feldman and Pentland, 2003). At the same time, heightened visibility may inhibit experimentation when actors avoid deviations that could be negatively interpreted by observers (Leonardi and Treem, 2020).

Dynamics are particularly salient in the context of **emergent processes**, which cannot be fully predefined but instead unfold during execution. Such processes are typically knowledge-intensive, context-dependent, and characterized by uncertainty and deliberation. Marjanovic (2005) describes emergent business processes as unstructurable, as their structure evolves from accumulated experience rather than being specified upfront. From a routine dynamics perspective, emergence results from the mutually constitutive relationship between ostensive aspects, such as process models, and performative enactments that may deviate and thereby reshape the process over time (Feldman and Pentland, 2003; Beverungen, 2014).

Building on this view, Mahringer and Walleser (2023) theorize how process mining affects emergent aspects of processes by conceptualizing process models as artifacts that provide impulses for change rather than instruments of deterministic control. Process mining makes patterns of action visible to participants and thereby shapes sensemaking and enactment. Two mechanisms are identified: focusing, where actors converge on selected paths, and exploring, where visualized variability encourages experimentation. In this way, process mining does not suppress emergence but actively mediates process dynamics (Feldman, 2000; Pentland, Liu, et al., 2020).

In computer science and process mining, dynamics are frequently conceptualized as **process** or **concept drift**. This perspective focuses on how dominant execution patterns evolve over time due to endogenous developments or exogenous events (Bose et al., 2014; Röglinger et al., 2022). Drift becomes observable in event data as shifting variants (Suriadi et al., 2014), deviations (König et al., 2019), or workarounds (Soffer et al., 2023). Rather than embedding anticipated change into process designs, this line of research emphasizes detecting and analyzing empirically observed changes in behavior (Grisold, Janiesch, et al., 2024).

Concept drift originates from machine learning and data mining and denotes changes in the underlying data-generating process such that models learned from historical data no longer represent current behavior (Schlimmer and Granger, 1986). In process mining, drift concerns changes in complex behavioral structures, including control-flow, data usage, and resource allocation (Bose et al., 2014). Different drift types can be distinguished, including sudden, gradual, recurring, and incremental drift, which may occur in combination and challenge assumptions of long-term process stability (Bose et al., 2014; Kraus and van der Aa, 2026).

Overall, the presented concepts illustrate that dynamics in BPM research do not represent a single, unified concept. Instead, they span operational and contextual levels of analysis and range from relatively predictable process changes to open-ended, uncertain transformations. Grisold, Janiesch, et al. (2024) argue that recognizing these different meanings is essential for developing an integrative understanding of how dynamics in and around business processes can be analyzed and managed.

### 2.1.3 Knowledge Intensive Processes as Intended Dynamic Behavior

Knowledge-intensive processes (KIPs) constitute a distinct class of organizational processes characterized by a high degree of uncertainty, variability, and reliance on expert judgment (Di Ciccio et al., 2015; Isik et al., 2012). They are defined as "*processes whose conduct and execution are heavily dependent on knowledge workers performing various interconnected, knowledge-intensive decision-making tasks. KIPs are genuinely knowledge, information, and data-centric and require substantial flexibility at design- and run-time*" (Di Ciccio et al., 2015, p. 5). Typical industrial examples include product development and innovation processes, where ideas and concepts are iteratively refined into market-ready products. These processes are strategically important because they shape organizational innovation capabilities and sustained competitive advantage (Eppler et al., 1999; de Almeida Rodrigues Gonçalves et al., 2023; Khanbabaei et al., 2019; Ramesh and Tiwana, 1999).

KIPs are inherently difficult to predict (Isik et al., 2012; Marjanovic and Freeze, 2011), digitize, and standardize (Isik et al., 2012). This difficulty stems from their complexity, the flexibility they require (Eppler et al., 1999; Isik et al., 2012; Vaculin et al., 2011), and the ambiguity of their inputs and outputs (Di Ciccio et al., 2015). Human-centered activities play a central role in KIPs (Di Ciccio et al., 2015; Marjanovic and Freeze, 2011), enabling creativity and innovation (Khanbabaei et al., 2019) while increasing process variability. Task sequences often emerge dynamically (Marjanovic, 2005) based on individual decisions, situational factors, and unforeseen events (Di Ciccio et al., 2015). Consequently, each process instance reflects the situated actions and judgments of its participants (Di Ciccio et al., 2015; Isik et al., 2012; Eppler et al., 1999; Gronau and Weber, 2004; Campos et al., 2018). The strong involvement of human actors is therefore a primary source of KIPs' complexity (de Almeida Rodrigues Gonçalves et al., 2023), complicating their representation in predefined process models (Di Ciccio et al., 2015) and producing a large number of process variants (Di Ciccio et al., 2015; Eppler et al., 1999; Isik et al., 2012; Gronau and Weber, 2004). Moreover, KIPs frequently involve unplanned knowledge creation activities (Di Ciccio et al., 2015), making each execution highly dependent on in-situ decisions and experiential knowledge (Di Ciccio et al., 2015; Isik et al., 2012; Eppler et al., 1999; Gronau and Weber, 2004; de Almeida Rodrigues Gonçalves et al., 2023). KIPs therefore represent strong examples of light-touch processes that adopt flexibility-by-design while requiring substantial infrastructural flexibility to prosper (Schonenberg et al., 2008; Baiyere et al., 2020).

From an organizational perspective, the ability to create, disseminate, and integrate knowledge into products and services is a key determinant of long-term success (Ramesh and Tiwana, 1999). Knowledge creation is inherently a social process that depends on individuals, as organizations cannot generate knowledge independently of their members (Nonaka and von Krogh, 2009). Consequently, process participants' knowledge must be accessed, shared, and integrated into organizational knowledge systems to support effective execution and continuous improvement (Bhatt, 2001).

The theory of organizational knowledge creation, particularly the **SECI** (**S**ocialization, **E**xternalization, **C**ombination, **I**nternalization) model (Nonaka and Takeuchi, 1995), provides a strong conceptual foundation for understanding knowledge dynamics in KIPs. At its core, the SECI model emphasizes the continuous transformation between tacit and explicit knowledge as the basis of organizational knowledge creation (Nonaka and Takeuchi, 1995). To expand knowledge beyond individuals and amplify it across organizational levels, tacit knowledge must be articulated and made explicit (Nonaka and von Krogh, 2009). Compared to other knowledge management approaches that capture only partial aspects of knowledge dynamics (e.g., Zack (1999) and Choo (1996)), the SECI model systematically conceptualizes bidirectional knowledge conversion and multi-level knowledge amplification (Nonaka and Takeuchi, 1995), making it particularly suitable for analyzing KIPs.

The SECI model distinguishes four modes of knowledge conversion: *socialization*, *externalization*, *combination*, and *internalization* (Nonaka and Takeuchi, 1995; Nonaka et al., 2000). Socialization refers to the sharing of tacit knowledge through direct interaction and shared experience, externalization describes the articulation of tacit knowledge into explicit forms such as concepts or documents, combination denotes the integration and recombination of explicit knowledge, and internalization captures the process through which individuals absorb explicit knowledge and transform it into tacit knowledge through practice and experience. In KIPs such as product development, tacit knowledge is shared through collaboration and informal interaction, articulated through reflection and documentation, combined with existing explicit knowledge sources, and internalized through learning-by-doing. These modes collectively enable organizational learning that transcends individuals and departments, beginning with personal experience and expanding into organization-wide knowledge structures (Nonaka and Takeuchi, 1995; Nonaka et al., 2000; Ramesh and Tiwana, 1999).

A key distinction in KIPs lies between explicit and tacit process-related knowledge (Ramesh and Tiwana, 1999). Explicit knowledge can be articulated, documented, and shared in symbolic form, whereas tacit knowledge is personal, context-specific, and embedded in individuals' experiences, skills, and judgment (Polanyi, 1967; Nonaka and Takeuchi, 1995). In KIPs, tacit process-related knowledge plays a central role, as participants continuously adapt their actions based on situational understanding and experiential insight (Di Ciccio et al., 2015). While parts of this knowledge can be externalized and integrated into organizational practices (Davenport and Prusak, 1998), a substantial portion remains difficult to formalize and is therefore rarely disseminated across the organization (Di Ciccio et al., 2015). This limitation constrains organizational learning and reduces the ability to systematically leverage experiential insights from individual process executions (Gronau and Weber, 2004; Isik et al., 2012).

Finally, KIPs challenge traditional notions of process improvement that emphasize standardization and conformity. In many cases, deviations from predefined norms reflect deliberate and well-reasoned decisions rather than inefficiencies (Di Ciccio et al., 2015). Understanding such deviations is essential for learning in KIPs, as value creation often emerges from context-specific problem solving rather than strict adherence to standard procedures. Consequently, fostering knowledge creation in KIPs requires mechanisms that capture not only what actions are taken but also why they are taken, thereby supporting reflection, learning, and continuous innovation across process instances. From a process dynamics perspective, KIPs represent a class of processes in which dynamic behavior is intended and desirable rather than something that should be strictly controlled.

Despite the growing body of research on KIPs, several challenges remain insufficiently addressed. The inherent variability and situational decision-making that characterize KIPs make it difficult for organizations to obtain systematic transparency over how such processes are actually executed in practice (Di Ciccio et al., 2015; Isik et al., 2012; Marjanovic and Freeze, 2011). Many adaptations, improvisations, and context-specific decisions occur locally during execution and therefore remain largely invisible at the organizational level (Di Ciccio et al., 2015; Gronau and Weber, 2004). This lack of visibility constrains organizations' ability to learn from past executions, identify recurring patterns of adaptation, or distinguish beneficial innovations from inefficient deviations (Gronau and Weber, 2004; Isik et al., 2012).

Despite these insights, significant challenges remain in empirically observing and analyzing the dynamic execution of KIPs Process mining provides a promising avenue in this regard, as it enables the reconstruction and analysis of actual process executions based on event data recorded in information systems (van der Aalst, 2016; van der Aalst, 2022). By making executions transparent, process mining can uncover hidden dynamics, identify recurring patterns of decision-making and adaptation, and provide evidence-based insights into how processes evolve over time (van der Aalst, 2016). However, applying process mining in such contexts remains challenging because many existing techniques assume relatively structured and repetitive processes with clearly defined event data (Di Ciccio et al., 2015; van der Aalst, 2016). The high variability, partial digitalization, and knowledge-driven nature of KIPs therefore call for new approaches that better capture and analyze dynamic, human-centered process behavior (Di Ciccio et al., 2015; Isik et al., 2012).

### 2.1.4 Workarounds as Unintended Dynamic Behavior

Workarounds constitute a central mechanism through which discrepancies between formally specified processes, recorded event data, and actual work practices arise (Alter, 2014), thus representing a flexibility-by-deviation approach (Schonenberg et al., 2008). They can be understood as intentional, goal-oriented deviations from prescribed procedures that enable actors to continue working when a *path is blocked* by obstacles, misalignments, or constraints (Ejnefjäll and Ågerfalk, 2019). More formally, workarounds are defined as *"goal-driven adaptations, improvisations, or changes to one or more aspects of an existing work system [to] overcome, bypass, or minimize the impact of obstacles, exceptions, anomalies, mishaps, established practices, management expectations, or structural constraints"* (Alter, 2014, p. 1044). As such, workarounds represent an emergent phenomenon in everyday organizational work (Alter, 2014), which has only recently begun to receive increased attention in the IS community (Ejnefjäll et al., 2023).

This definition highlights two essential characteristics. First, workarounds are purposeful rather than accidental; they are enacted consciously by the respective process participant to ensure continued business operations and to achieve specific goals such as efficiency, effectiveness, or compliance with competing demands (Röder et al., 2015). Second, workarounds inherently diverge from the prescribed process model, routine, or IT-supported procedure. As a consequence, every workaround introduces a mismatch between the formal process specification and actual execution, even when outcomes align with organizational objectives (Alter, 2014; Ejnefjäll and Ågerfalk, 2019).

Workarounds typically emerge in response to perceived misfits between formal standard operating procedures, supporting IT artifacts, and the realities of day-to-day work (Alter, 2014). Such obstacles may stem from regulatory or normative pressures (van Beijsterveld and van Groenendaal, 2016), company-specific constraints, or individual limitations such as missing resources, missing competencies, or insufficient system support (Choudrie and Zamani, 2016). Prior research distinguishes between strategic misfits between information systems and business processes (Gasser, 1986), technology misfits rooted in system properties (Strong and Volkoff, 2010), and organizational misfits arising from conflicting top-down and bottom-up pressures (Ejnefjäll and Ågerfalk, 2019; Bartelheimer et al., 2023). When prescribed processes cannot be executed as intended, employees diagnose their environment and improvise ad hoc solutions that allow them to complete their tasks despite existing constraints (Miller et al., 2012).

These early workarounds are often experimental, shaped by trial-and-error learning and individual judgment. They may involve bypassing or reordering process steps, substituting or adding activities, or using IT systems in unintended ways, including avoiding system use altogether or relying on alternative means to accomplish work (Gasser, 1986; Outmazgin and Soffer, 2016; Alter, 2015). In this sense, workarounds resemble a form of bricolage, in which actors recombine existing work elements to achieve specific goals under situational constraints (Malaurent and Karanasios, 2019). Over time, repeated enactment can lead to the routinization of previously exceptional behavior, rendering workarounds observable beyond the individual level through social learning, communication, or digital traces in organizational information systems (Alter, 2014; Leonardi and Treem, 2020).

As workarounds become visible to others (Leonardi and Treem, 2020), they may diffuse bottom-up across organizational units through observation, imitation, and informal communication (Bartelheimer et al., 2023). Colleagues encountering similar obstacles may adopt an existing workaround rather than developing a new solution themselves, allowing localized deviations to spread horizontally across processes and vertically across hierarchical levels (Alter, 2014). Although workarounds do not resolve the underlying misfit, they provide an alternative path toward work goals and can be understood as a form of secondary design, in which system functions and process content emerge during use rather than through formal planning (Alter, 2015; Germonprez et al., 2011).

Organizational awareness of recurring workarounds can trigger more deliberate responses. In some cases, management recognizes a workaround as a viable solution to a systemic problem and initiates a formal process improvement or redesign effort (Beerepoot and Van de Weerd, 2018). Through such initiatives, workarounds may be institutionalized and integrated into officially sanctioned to-be process models. This progression—from improvisation to routinization and eventual institutionalization—reflects a broader process of organizational learning and bottom-up process innovation (Nonaka and Takeuchi, 1995; Alter, 2014) and aligns with established BPM lifecycle approaches (Dumas et al., 2018).

The consequences of workarounds are ambivalent. On the positive side, they can sustain productivity, increase flexibility, and uncover misalignments that signal opportunities for improvement and innovation (Bartelheimer et al., 2023; Li et al., 2017). On the negative side, workarounds may undermine managerial control, violate security requirements, introduce inefficiencies, or negatively affect subsequent work activities (Alojairi, 2017; Pinto et al., 2018; Arduin and Vieru, 2017). These effects are often examined in isolation, neglecting their interdependencies, diffusion dynamics, and long-term organizational implications (Beerepoot et al., 2019).

From a BPM perspective, systematically analyzing workarounds is therefore essential. IT-based artifacts, particularly process mining techniques, support the identification of workaround candidates by detecting deviations in event logs (Outmazgin and Soffer, 2016; Weinzierl et al., 2021; van der Waal, van de Weerd, et al., 2024; Wijnhoven et al., 2023), complemented by qualitative methods such as interviews (Beerepoot et al., 2019). However, not all deviations constitute workarounds; some reflect unintended or situated deviance that may nevertheless offer improvement potential (Outmazgin et al., 2023). Decision-making regarding workarounds remains challenging due to their multifaceted and delayed consequences, motivating structured evaluation approaches such as the Action Impact Matrix (Beerepoot and Van de Weerd, 2018) or affordance-based perspectives (Vollenberg et al., 2023).

Given that standardized processes struggle to adapt quickly to technological change and exogenous shocks (Breu et al., 2002; Röglinger et al., 2022), workarounds are likely to remain a persistent feature of organizational life. They represent an unintended form of dynamic behavior from a bottom-up perspective that is nonetheless necessary in certain situations. When enacted frequently enough, they may consolidate into organizational routines and trigger formal process redesign, thereby constituting a source of continuous, employee-driven innovation and *"change from within"* (Essén and Lindblad, 2013; Outmazgin and Soffer, 2016).

Despite growing attention, workarounds remain difficult to systematically observe and analyze. They often emerge locally and diffuse informally through interpersonal communication or imitation before becoming visible at an organizational level (Alter, 2014; Leonardi and Treem, 2020; Bartelheimer et al., 2023). Consequently, organizations frequently lack transparency regarding the prevalence and impact of such deviations. Moreover, workarounds rarely occur in isolation but are often interconnected through shared underlying misfits and cascading effects across activities, processes, and IT artifacts (Beerepoot and Van de Weerd, 2018; Beerepoot et al., 2019; Alter, 2015; Leonardi, 2011). Evaluating individual workarounds without considering these interdependencies can therefore lead to incomplete or misleading conclusions.

A further challenge concerns the dynamic nature of workarounds. Rather than representing isolated deviations, they evolve over time as they are enacted, refined, shared, and routinized across actors and organizational units (Alter, 2014; Malaurent and Karanasios, 2019; Leonardi and Treem, 2020). Through processes of learning and imitation, localized adaptations may gradually spread and become embedded in organizational routines or trigger formal redesign efforts (Beerepoot and Van de Weerd, 2018; Ejnefjäll and Ågerfalk, 2019). However, existing research has primarily relied on conceptual work and qualitative case studies (Ejnefjäll et al., 2023; Alter, 2014), leaving open questions regarding how workaround dynamics unfold longitudinally, how they diffuse across processes, and how they interact with other forms of process change (Beerepoot et al., 2019).

Process mining offers a promising avenue for addressing these challenges by enabling the systematic analysis of deviations captured in event logs of information systems (van der Aalst, 2016; van der Aalst, 2022). Such data allow researchers to detect recurring deviations, analyze their temporal development, and examine their propagation across cases, activities, and organizational units (Outmazgin and Soffer, 2016; Weinzierl et al., 2021; Wijnhoven et al., 2023; van der Waal, van de Weerd, et al., 2024). At the same time, event logs capture observable behavior but rarely reveal the intentions or contextual constraints underlying a workaround (Beerepoot et al., 2019; Outmazgin et al., 2023). Advancing research therefore requires integrating process mining with qualitative approaches to identify, interpret, and evaluate workaround dynamics in their organizational context.

## 2.2 Process Mining and its Application on Dynamic Processes

### 2.2.1 Foundations of Process Mining

Process mining represents the state-of-the-art, data-driven method for analyzing processes. Since its inception in the 2000s (van der Aalst et al., 2004; van der Aalst et al., 2003) and the publication of the influential Process Mining Manifesto in 2012 (IEEE Task Force on Process Mining, 2012), this research discipline has formed a bridge between BPM and data science (van der Aalst, 2022). It has gained traction in research, with numerous scientific contributions published each year (Akhramovich et al., 2024; De Roock and Martin, 2022), and in practice, where software companies such as Celonis or Signavio are driving its commercial adoption (Deloitte, 2025). At its core lies digital trace data created during the execution of processes. These traces are typically captured by the information systems employed in organizations, such as ERP or CRM systems, or even dedicated business process management systems (van der Aalst, 2022). After extraction from such systems, the data is transformed into an event log, which records activities and events in a trace-wise manner (Buijs et al., 2014). Including timestamps and additional process-specific data, the event log can then be used to apply various process mining techniques, such as process discovery, conformance checking, performance analysis, comparative process mining, predictive process mining, and action-oriented process mining (see Figure 2.1) (van der Aalst, 2022).

With these techniques, process mining promises to be a significant tool within the BPM lifecycle (van der Aalst, 2016; Dumas et al., 2018). It can help organizations discover the current state of their processes, including the revelation of bottlenecks, inefficiencies, and data quality issues. Traditionally, process mining approaches

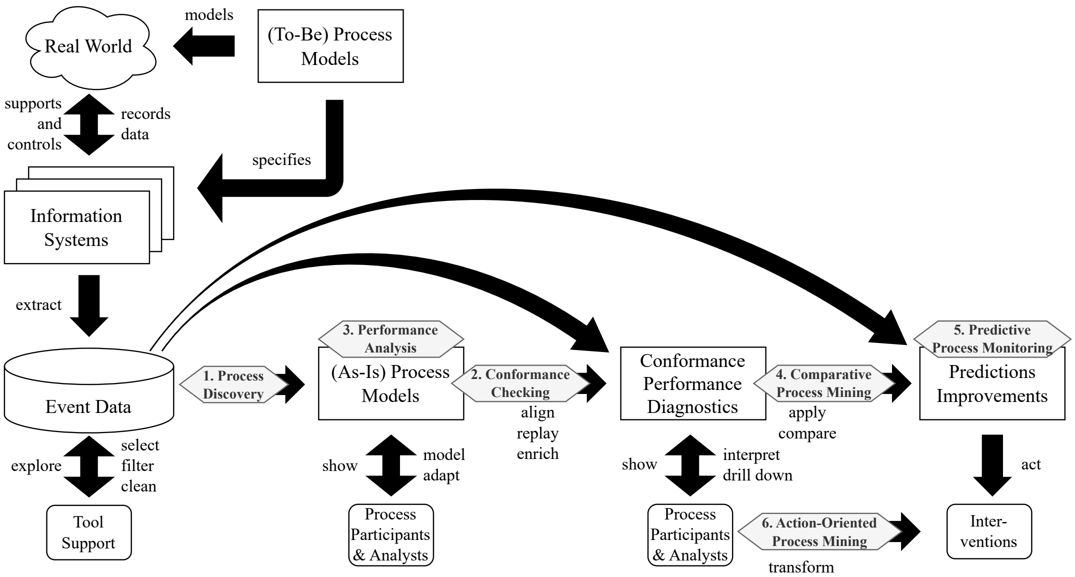


**Figure 2.1:** Process Mining Framework (adapted from van der Aalst (2016) and van der Aalst and Carmona (2022))

have acted primarily retrospectively, but recent techniques, such as action-oriented process mining, aim to provide live insights into processes to enable ad-hoc decision-making (van der Aalst, 2022; Park and van der Aalst, 2022). This capability is particularly valuable given the increasingly dynamic nature of organizations and processes, whether due to endogenous changes (Andrews, Suriadi, Wynn, et al., 2018), such as the onboarding of new employees, or exogenous shocks, such as the COVID-19 pandemic (Röglinger et al., 2022). Nonetheless, organizations still struggle to leverage process mining to create value (Badakhshan et al., 2022), as they face numerous organizational hurdles, such as a lack of management support, as well as technical challenges, such as poor data quality (Martin et al., 2021).

One recent but major paradigm shift in process mining is the transition from a case-centric perspective to an object-centric perspective, giving rise to the subdiscipline of *object-centric process mining* (OCPM) (van der Aalst, 2023). Traditional process mining relies on event logs with a strictly hierarchical structure consisting of processes, traces, and events, where each event is associated with exactly one case representing an instantiation of a specific process type (van der Aalst and Carmona, 2022). While this representation has enabled many successful analysis techniques, it assumes that events can be uniquely assigned to a single case. In practice, however, business activities frequently involve multiple interacting entities—such as orders, invoices, products, or employees—making it difficult to adequately represent such interactions within a single-case structure.

Object-centric process mining addresses this limitation by shifting the analytical focus from cases to business objects and their relationships (Berti and van der Aalst, 2023). Instead of assigning each event to one trace, object-centric event logs allow events to be linked to multiple objects of different types, thereby capturing the interactions that characterize real organizational processes (see Table 2.2). To support this perspective, the *Object-Centric Event Log* (OCEL) format records events together with the objects they reference and the relations between them (van der Aalst, 2019; Berti and van der Aalst, 2023). This representation enables the analysis of processes across interacting objects and process instances, thereby making organizational dynamics more visible.

At the same time, the object-centric perspective introduces methodological challenges. Because most existing process mining techniques assume a case-centric structure, object-centric logs are sometimes flattened into traditional event logs by selecting one object type as the case notion (Berti and van der Aalst, 2023). However, this transformation can lead to problems such as *convergence*, where the same event appears multiple times within a trace, and *divergence*, where events appear in incorrect temporal order (van der Aalst, 2019). Moreover, abandoning a clear case notion complicates the application of techniques that rely on sequential event structures. Recent research therefore proposes hybrid solutions, such as advanced case notions that preserve most object interactions while reducing convergence and divergence issues (van Detten et al., 2025). These developments are particularly relevant for studying phenomena that unfold across multiple cases or interacting objects—such as interconnected workarounds—thereby highlighting the potential of OCPM for identifying cross-case and cross-process dynamics in organizational processes.

### 2.2.2 Process Mining of Knowledge-Intensive Processes

Established process mining approaches are primarily effective in highly digitalized and standardized process environments, as they rely on large volumes of accurate and structured event data (IEEE Task Force on Process Mining, 2012; van der Aalst and Carmona, 2022). Many organizational processes, however, deviate from these

**Table 2.2:** Comparison of Traditional and Object-Centric Process Mining

| **Aspect** | **Traditional Process Mining (Case-Centric)** | **Object-Centric Process Mining (OCPM)** | **Sources** |
|---|---|---|---|
| Core perspective | Focuses on a single case notion where each process instance corresponds to one case (e.g., order or claim). | Focuses on multiple interacting business objects that jointly shape process execution. | van der Aalst (2023) and Berti and van der Aalst (2023) |
| Event-log structure | Each event refers to exactly one case identifier. | Events can be associated with multiple objects and object types simultaneously. | Berti and van der Aalst (2023) |
| Data representation | Events are organized as linear traces per case, forming a sequence of activities. | Events are represented as object-centric event logs capturing relationships between objects. | van der Aalst (2023) and Berti and van der Aalst (2023) |
| Handling real-world complexity | Limited ability to represent many-to-many relationships between entities. | Naturally captures complex interactions between multiple objects in enterprise processes. | van der Aalst (2023) |
| Process view | Provides a case-centric view focusing on a single process instance type. | Provides a multi-dimensional view across interacting objects and processes. | van der Aalst (2023) |
| Typical application contexts | Works well for structured processes with clear case identifiers. | Suitable for complex enterprise environments with interacting entities. | van der Aalst (2023) and Berti and van der Aalst (2023) |

assumptions and exhibit low degrees of structure, predictability, and formalization (Di Ciccio et al., 2015; Isik et al., 2012; Eppler et al., 1999; Gronau and Weber, 2004). From a process mining perspective, KIPs therefore pose substantial challenges.

Only a limited body of research has explicitly addressed how process mining can be adapted to the characteristics of KIPs. Existing studies propose extensions such as mining speech-act flows from event data to support performance analysis in knowledge-intensive settings (Richetti et al., 2017), or applying clustering and classification techniques to uncover latent patterns and derive improvement recommendations (Khanbabaei et al., 2019). Other contributions focus on design-oriented support, for example by mining and recommending templates for new KIPs within agenda-driven case management (Benner-Wickner et al., 2015) or by leveraging experience from previously handled cases through recommendation systems (Terziev et al., 2015). In manufacturing, process mining has been applied to product innovation contexts, such as analyzing maintenance operations in cellular manufacturing (Dunzer et al., 2021), combining process mining with case-based reasoning (Berriche et al., 2015), or integrating natural language processing techniques to predict lead times (Brennig, Benkert, et al., 2024). Beyond industrial domains, applications in healthcare examine diagnostic, treatment, and organizational work (Munoz-Gama et al., 2022).

While these studies broaden the application landscape of process mining, they largely remain grounded in event-log-based representations of process execution. As a result, they predominantly capture explicit process-related knowledge and provide only limited access to participants' experiential knowledge, skills, and situated decision-making—factors that constitute the core drivers of KIPs (Di Ciccio et al., 2015). This limitation highlights a fundamental gap in current research and motivates the need for process mining approaches that more adequately account for the knowledge-intensive and human-centered nature of such processes.

### 2.2.3 Data-driven Identification of Workarounds with Process Mining

The identification of workarounds forms the first logical step in managing them. Prior research distinguishes between qualitative and quantitative approaches for workaround detection (Beerepoot and Van de Weerd, 2018). Qualitative methods, such as interviews and observations, are well established and effective in uncovering workarounds and other deviations in process execution (Beerepoot et al., 2019; Mörike, 2022; Van de Weerd et al., 2018). However, due to their resource-intensive nature and focus on specific points in time, they are ill-suited for continuous monitoring. This limitation constrains their scalability in organizational contexts and motivates the development of (semi-)automated, data-driven approaches capable of leveraging digital traces of process execution.

Quantitative approaches utilize data traces from information systems to identify workaround candidates through the analysis of event data and additional contextual information. Early work already emphasized the importance of domain knowledge and the inherent difficulty of distinguishing meaningful deviations from noise in event logs (Outmazgin and Soffer, 2013). More recent approaches explicitly target workaround detection. For instance, Weinzierl et al. (2021) propose a deep learning–based method that identifies control-flow deviations and evaluate it on synthetically enriched event logs with manually labeled workarounds. While promising, such approaches depend on the availability of labeled training data, which is rarely available in practice and therefore limits their applicability in real-world organizational settings.

The most comprehensive data-driven approach to date is the **S**emi-automated **WOR**karound **D**etection (**SWORD**) framework (van der Waal et al., 2022; van der Waal, van de Weerd, et al., 2024; van der Waal, Kappen, et al., 2024; Outmazgin et al., 2023). SWORD operationalizes workaround detection through 22 predefined patterns derived from empirical studies in healthcare and retail. These patterns are grouped into four categories—"Control Flow", "Data", "Resource", and "Time"—and are designed to flag common deviations from the intended process model, such as unexpected activities, out-of-range data values, or atypical resource assignments. A key limitation of the framework is that pattern matches merely indicate potential workarounds; final validation and interpretation remain the responsibility of domain experts. Subsequent refinements aim to mitigate this limitation by improving pattern prioritization, supporting ex-post evaluations of deviation strength and usefulness, and optimizing expert involvement (van der Waal, van de Weerd, et al., 2024). Empirical applications, however, have so far focused primarily on healthcare and public administration (van der Waal, van de Weerd, et al., 2024; van der Waal, Kappen, et al., 2024), leaving questions about generalizability across domains largely unexplored.

Related work by Dubinsky et al. (2023) investigates cross-case associations, albeit within a traditional case-centric perspective. More broadly, most existing detection approaches operate on individual process cases and assume a single-case event log structure. This assumption limits their ability to capture interactions between multiple objects, cases, or processes, even though recent research highlights that workarounds often emerge from systemic misfits and may propagate across organizational processes (Alter, 2014). As a result, the interconnected and potentially cross-process nature of workarounds remains insufficiently reflected in current quantitative detection methods.

Overall, existing research demonstrates the feasibility of identifying workaround candidates using event data, but also highlights persistent challenges related to data quality, model availability, domain dependence, and validation effort (van der Waal, van de Weerd, et al., 2024). Moreover, current approaches remain largely constrained to case-centric perspectives and isolated deviation patterns (Dubinsky et al., 2023). As a result, they primarily focus on identifying deviations from expected process behavior rather than systematically examining the data manifestations of workarounds themselves. However, workarounds do not only alter control-flow behavior; they often affect multiple dimensions of process execution, including resource assignments, timestamps, and data attributes. This also includes workarounds, which are not recorded by any information system (Beverungen, 2014; Bartelheimer et al., 2023). Understanding which observable patterns in event data are systematically caused by workaround behavior therefore remains an open challenge. Without such knowledge, distinguishing workaround-induced deviations from routine variability or noise remains difficult. Consequently, further research is required to better understand the characteristic data footprints of workarounds and to develop scalable, context-aware detection approaches that can capture these patterns across interacting objects and processes (Leonardi, 2011). Advances in object-centric process mining, which explicitly capture relationships between multiple process objects within event data (van der Aalst, 2019), provide a promising foundation for addressing this challenge and enabling more holistic data-driven identification of workarounds in complex organizational environments.

## 2.3 Process Science

To varying degrees, capturing dynamics and change in processes has been a part of BPM research for a long time (Rescher, 1996; Beverungen, 2014; Pentland, Liu, et al., 2020; Röglinger et al., 2022). As the world changes at an ever increasing speed, corresponding movements within the BPM community became apparent, notably under the term of process science. The term *Process Science*, however, has been used in prior research with varying emphases (vom Brocke et al., 2024). In the computer science domain, it has been defined as "*the broader discipline that combines knowledge from information technology and knowledge from management sciences to improve and run operational processes*" (van der Aalst and Damiani, 2015, p. 2). Similarly, Mendling (2016) uses the term to call for more rigorous scientific and empirical research in BPM. The definition adopted in this dissertation is provided by vom Brocke et al. (2024), who conceptualize process science as "*the interdisciplinary study of socio-technical processes over time*". Socio-technical processes are understood as coherent series of changes involving both human and technological actions across multiple levels. While the consideration of change and dynamics is not entirely new within BPM and related disciplines (Rescher, 1996; Beverungen, 2014; Grisold, Janiesch, et al., 2024), the renewed emphasis on change over time captures the essence of dynamic processes and provides a suitable foundation for positioning the contributions of this dissertation (see Section 4.2).

Process science is grounded in four key tenets (vom Brocke et al., 2024): **(1)** socio-technical processes are the focus; **(2)** socio-technical processes are investigated scientifically; **(3)** investigation occurs through an interdisciplinary lens; and **(4)** process science aims to change processes and create practical impact.

The **first** tenet, *"socio-technical processes are the focus"*, calls for prioritizing processes over entities. While computer science and IS research traditionally view processes as changes to pre-existing entities (Wand and Weber, 1993), other perspectives emphasize processes as foundational. Although processes and entities are interdependent, a process-centric perspective facilitates the analysis of change and its effects across domains. Process science focuses specifically on socio-technical processes, which may differ in structure, form, outcome, language, and origin (Rescher, 2000). Depending on these characteristics, organizational or technical perspectives may dominate. A further distinction concerns ownership: owned processes involve agency (Leonardi, 2011) and intention, whereas unowned processes unfold without agency; nevertheless, both influence each other (Rescher, 2000). This distinction extends to activities and events, where internal factors may be shaped by process owners, while external events must be accommodated (vom Brocke et al., 2024). A similar focus has already been proposed in the past by Beverungen (2014), where social and technical aspects influence each other and thus the shape of the process.

The **second** tenet, *"socio-technical processes are investigated scientifically"*, emphasizes systematic inquiry through deduction, induction, and abduction, with a focus on causal–temporal relationships. Process science distinguishes three core activities: *Discovery*, *Explanation*, and *Intervention*. *Discovery* focuses on identifying (emergent) dynamics underlying a focal phenomenon, primarily through retrospective analysis of digital trace data (Lazer et al., 2020). Analogous to process discovery in process mining, it addresses the *how* of process behavior, for example by deriving process models or identifying patterns. *Explanation* addresses the *why* by uncovering cause–effect relationships in context. While digital trace data remains central, contextual understanding—often supported by domain experts—is essential. Predictive techniques, such as predictive process monitoring (Marquez-Chamorro et al., 2018), can be employed to anticipate future process states, complemented by qualitative methods such as interviews or observations. *Intervention* aims to deliberately change ongoing processes to address real-world problems (Gaieck et al., 2020; Oliver et al., 2020; Rosen, 2018). Interventions should be grounded in the causal mechanisms identified through explanation. Design-oriented approaches, particularly Design Science Research (Hevner et al., 2004), are well suited to derive prescriptions for process change through technological or organizational means. While all three activities are integral to process science, individual studies may focus on only a subset.

Process science draws on event data from digital traces (e.g., social media or production systems) (van der Aalst, 2016) as well as qualitative data sources (Myers and Newman, 2007). Capturing the interplay of processes requires data across multiple levels of abstraction (Rescher, 2000). In this context, object-centric process mining extends traditional process mining by enabling the analysis of interactions between objects independently of predefined cases or process types (van der Aalst, 2023).

Inspired by the Design Science Research Framework (Hevner et al., 2004), the Process Science Research Framework (Figure 2.2) integrates the flow from process data to discovery, explanation, and intervention (vom Brocke et al., 2024). This core is complemented by an existing knowledge base, comprising theoretical foundations and methodological resources, as well as data from the investigated context, including people, tasks, and technologies. Research outcomes ideally contribute both to the focal context and to the broader knowledge base, which is also key to IS research (Hevner et al., 2004; Hevner, 2007).

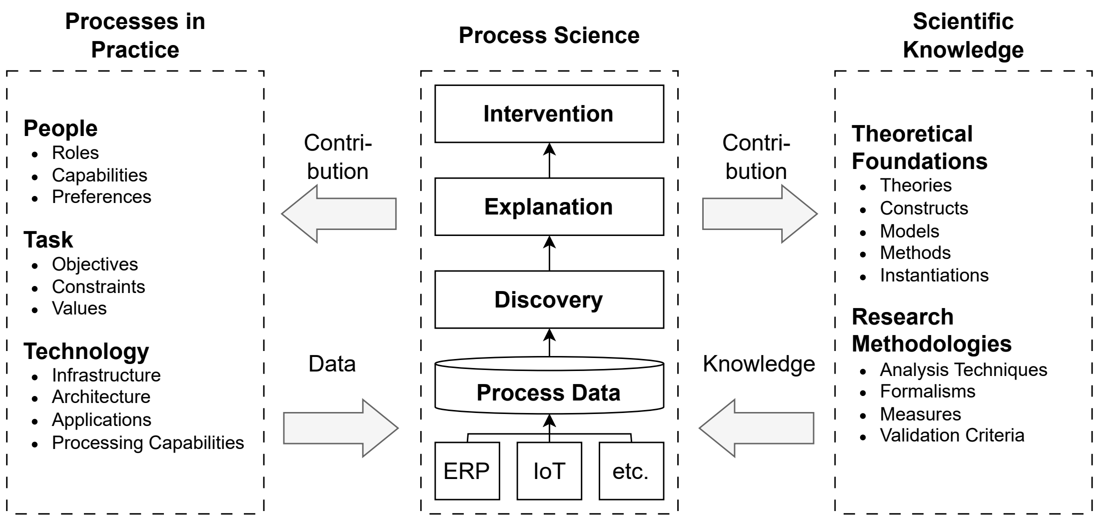


**Figure 2.2:** Process Science Research Framework (vom Brocke et al., 2024)

The **third** tenet, *"investigation occurs through an interdisciplinary lens"*, highlights the necessity of integrating perspectives beyond BPM. BPM has been characterized as a boundary-spanning research field that integrates managerial, organizational, and technological perspectives in the past (Rosemann and vom Brocke, 2015), but process science intends to push this cooperation further (vom Brocke et al., 2024). Addressing complex societal challenges—such as reducing environmental impacts—requires insights from business, economics, political science, the social sciences, and environmental studies (Hertz et al., 2020; J. Song et al., 2017). For instance, combining perspectives from routine dynamics and BPM allowed for a more wholistic understanding of workarounds (Alter, 2014; Ejnefjäll et al., 2023; Bartelheimer et al., 2023).

The **fourth** tenet, *"process science aims to change processes and create practical impact"*, emphasizes knowledge with instrumental value for solving real-world problems (Dewey and Rogers, 2012). Process science thus adopts a pragmatic orientation and explicitly encourages the study of both naturally evolving and intentionally designed processes (Pettigrew, 1997). This focus on impact is also in line with the positioning of DSR (Gregor and Hevner, 2013), further emphasizing the shared goals of IS and process science research.

# 3 Research Design

## 3.1 Design Science Research Paradigm

Information Systems (IS) research is fundamentally concerned with the interplay between technology, people, and organizations, and with understanding how these elements mutually shape one another in practice (March and Smith, 1995; Hevner et al., 2004). At its core, the discipline investigates how information systems are analyzed, designed, deployed, used, evaluated, and evolved to address complex organizational challenges (Hevner et al., 2004). Owing to its position at the intersection of organizational research and information technology research (Orlikowski and Barley, 2001), IS research is inherently interdisciplinary, integrating perspectives from computer science, management research, sociology, and psychology (Becker and Niehaves, 2007). A defining characteristic of the field is its socio-technical orientation: information systems cannot be understood as isolated technological artifacts but must be studied as embedded in—and co-evolving with—social and organizational contexts (Hevner et al., 2004; March and Smith, 1995; Sein et al., 2011). Consequently, IS research commonly starts from real-world problems and aims to generate contributions that are both theoretically meaningful and practically relevant (Gregor and Hevner, 2013; Hevner et al., 2004).

The creation of knowledge in IS research is dominated by two complementary paradigms: behavioral science and design science (Hevner et al., 2004; Goldkuhl, 2016). Behavioral science focuses on the development and justification of theories that explain, predict, or analyze phenomena related to the use and impact of information systems in organizations, corresponding to theory types I–IV in Gregor's typology (Gregor, 2006). In contrast, Design Science Research (DSR) as a paradigm addresses questions relevant to human and organizational problems through the purposeful design and evaluation of innovative artifacts, thereby contributing new knowledge to the scientific knowledge base (Hevner and Chatterjee, 2010; Deng and

Ji, 2018). Rather than primarily striving for truth in the explanatory sense, DSR is rooted in pragmatism and emphasizes utility—an artifact is considered valuable if it works effectively in addressing a relevant problem (Hevner et al., 2004; Goldkuhl, 2012). Nevertheless, rigorous IS research requires the integration of both paradigms, as design activities build on existing theories and empirical insights, while the evaluation of artifacts feeds back into the knowledge base (Hevner et al., 2004; Sein et al., 2011).

The widely adopted IS research framework (see Figure 3.1) by Hevner et al. (2004) conceptualizes research as operating within a context—originally termed the environment—comprising people, organizations, and technologies, which together form the problem space (Simon, 2019). Emerging needs and opportunities within this problem space motivate research efforts. Two intertwined cycles lie at the core of DSR: the build (or develop) cycle, in which artifacts are designed, and the evaluate (or justify) cycle, in which their utility, quality, and implications are assessed (March and Smith, 1995; Hevner et al., 2004). This iterative logic reflects the notion of *"learning through building"* (Kuechler and Vaishnavi, 2011, p. 126). In DSR, the problem space is often characterized by so-called wicked problems—problems that are complex, ill-defined, and evolving, such that proposed solutions may reshape the problem itself (Rittel and Webber, 1973; Hevner et al., 2004). Accordingly, context plays a central role by setting boundaries and requirements for artifact design and by influencing how artifacts can be meaningfully evaluated (Alexander, 1964; Simon, 2019; zur Heiden and Beverungen, 2022).

Within the DSR paradigm, research outputs take the form of IT artifacts, which may be constructs, models, methods, or instantiations (March and Smith, 1995; Hevner et al., 2004; Gregor and Hevner, 2013). Constructs define the key concepts and vocabulary of a domain, models specify relationships among these constructs, methods describe procedures or algorithms for achieving desired outcomes, and instantiations represent operational realizations of artifacts in specific settings (March and Smith, 1995). IT artifacts are not neutral or static; rather, they are shaped by stakeholder interests, embedded in specific contexts, composed of interrelated components, and continuously evolving through use and adaptation (Orlikowski and Barley, 2001). If artifacts prove useful—by addressing novel problems or by outperforming existing solutions—they contribute both practical value and theoretical insights to the IS knowledge base (Hevner et al., 2004; March and Smith, 1995). Beyond concrete artifacts, DSR also intends to yield more abstract forms of prescriptive knowledge,

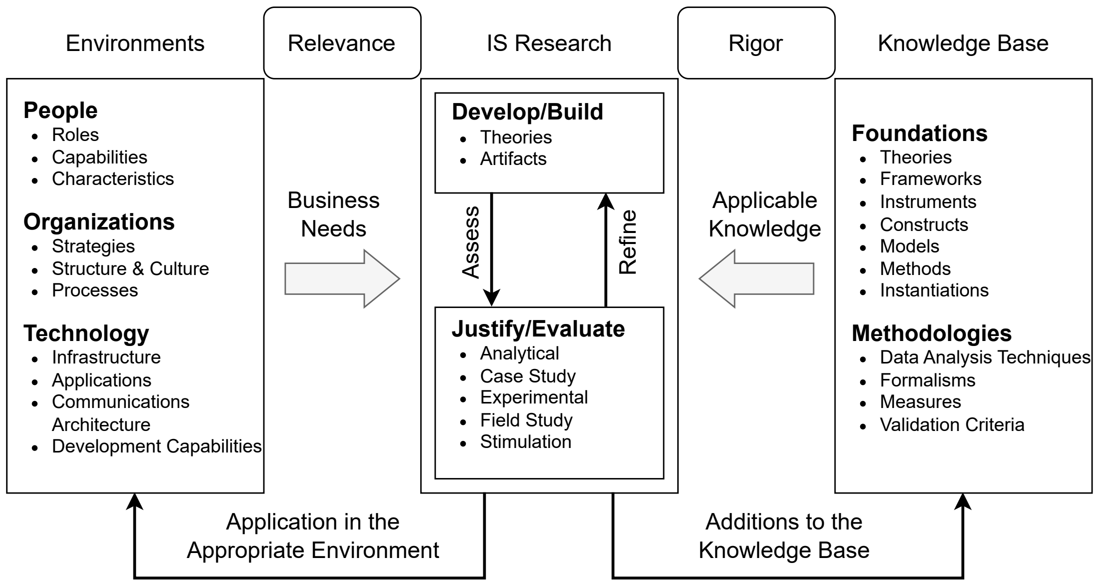


**Figure 3.1:** Design Science Research Framework (Hevner et al., 2004)

such as design principles or design theories, which inform future design and action (Gregor et al., 2020; Gregor and Hevner, 2013).

To distinguish substantive research contributions from routine design, Gregor and Hevner (2013) propose a classification based on the maturity of both the problem domain and the solution. Routine design applies well-established solutions to familiar problems and is generally not considered a significant research contribution. Improvement refers to novel or enhanced solutions for known problems, while exaptation denotes the transfer of mature solutions to new or adjacent problem domains. Invention represents the most radical contribution, involving fundamentally new solutions for previously unaddressed problems. This classification clarifies the diverse ways in which DSR can expand scientific knowledge while addressing practical challenges. In line with theories for design and action (type V) (Gregor, 2006), DSR thus emphasizes purposeful intervention, positioning IS research as a discipline that not only explains the world but actively contributes to shaping it.

### 3.1.1 Design Science Research Methodology

As DSR on its own is considered an overarching paradigm, concrete methods are required to operationalize this paradigm. One of the most widely used approaches in recent research is the Design Science Research Methodology (DSRM) (see Figure 3.2) proposed by Peffers et al. (2007). It offers an iterative six-step procedure that can be initiated from various entry points. Its iterative nature allows new insights to be incorporated during the research process while also respecting the cyclic nature of DSR (Hevner, 2007), albeit to a more limited extent compared to more recent approaches such as Action Design Research (Sein et al., 2011) or echeloned Design Science Research (Tuunanen et al., 2024).

The six steps of DSRM comprise (1) identify the problem and motivate, (2) define the objectives of a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication (Peffers et al., 2007). Depending on the context, one of the first four steps can serve as an entry point. For example, if a problem is already properly defined, researchers can immediately start with the second step. This was the case in paper **P5**, where the general problem of workaround identification had already been established by van der Waal, van de Weerd, et al. (2024). DSRM was also used in the subsequent paper **P6**, which builds upon the problems defined in P7 and P8, as well as the objectives formulated in P9.

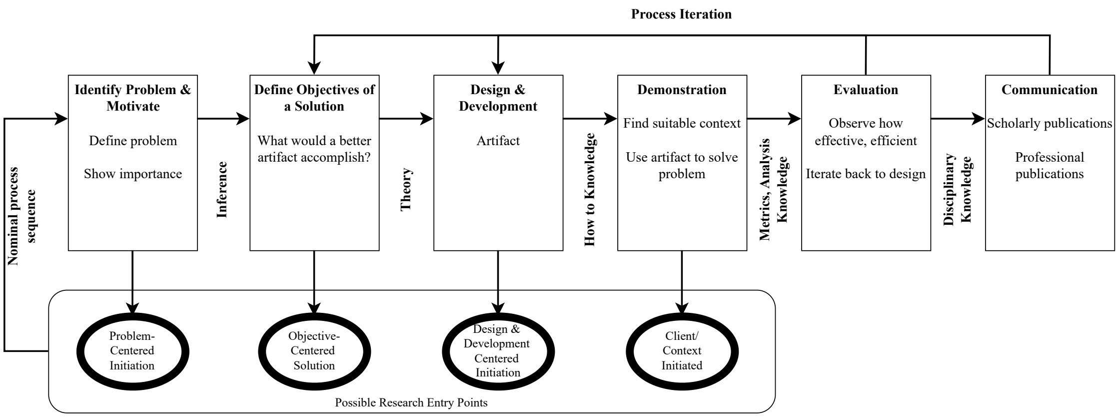


**Figure 3.2:** Design Science Research Methodology (Peffers et al., 2007)

### 3.1.2 Action Design Research

Action Design Research (ADR) is a design-oriented research approach that blends the construction-driven logic of DSR with the interventionist, iterative characteristics of action research (Sein et al., 2011). Its central premise is that effective design knowledge emerges when researchers engage directly with a real organizational problem while simultaneously constructing and evaluating an IT artifact intended to address a broader class of issues.

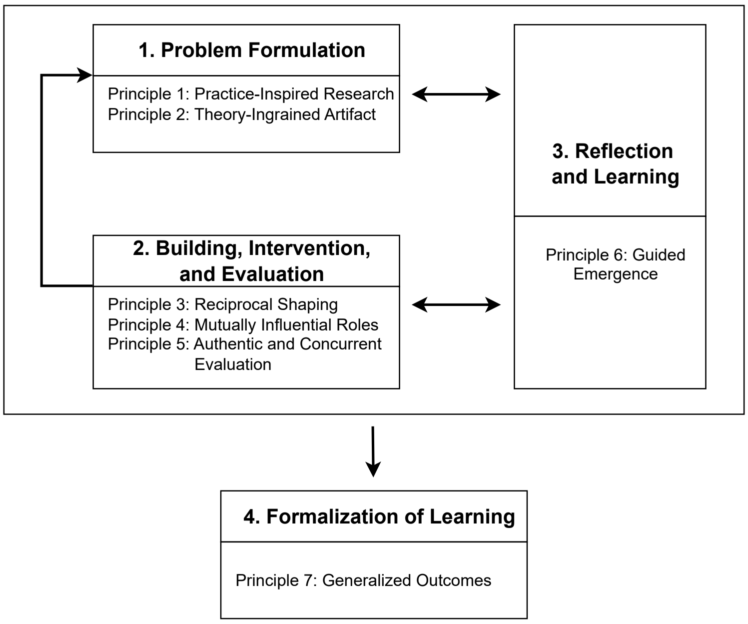


**Figure 3.3:** Action Design Research (Sein et al., 2011)

The method (see Figure 3.3) begins with the (1) Problem Formulation, during which the research team investigates an immediate practical setting to understand the problem space, identify relevant theories, and shape an initial set of design goals that have the potential to generalize beyond the single case. Based on this grounding, the process moves into the (2) Building, Intervention, and Evaluation (BIE) phase, where the artifact is iteratively designed and repeatedly introduced into the organizational environment. In this stage, design decisions and evaluation activities occur concurrently rather than sequentially, allowing the artifact to be shaped by practical constraints, user feedback, and emergent organizational dynamics as it evolves. Throughout these activities, the (3) Reflection and Learning stage runs in parallel: researchers continually reassess the problem framing, the assumptions guiding the design, and the insights gained from interventions, using this reflection to steer ongoing development and refine theoretical understanding. Finally, the (4) Formalization of Learning phase abstracts the context-specific insights into more generalizable outcomes, such as design principles (Gregor et al., 2020) or design theories (Gregor and Hevner, 2013) that capture how and why the artifact addresses the identified class of problems. Taken together, these four stages emphasize the iterative and collaborative nature of ADR, which avoids the rigid separation of design and evaluation found in other DSR approaches (e.g., Peffers et al., 2007) and instead foregrounds organizational interventions and researcher participation as essential mechanisms for generating robust design knowledge (Sein et al., 2011).

This approach was primarily leveraged in paper **P4**, as close cooperation with two case companies was essential. Both researchers and practitioners actively shaped the design of the ensemble artifact, while the participating organizations' contexts informed the general assumptions and requirements. Furthermore, while three major iterative cycles were conducted, numerous micro-iterations took place within these cycles to arrive at the final artifact and its associated design principles. To ensure the reusability of the design principles, five criteria were employed: (1) accessibility, (2) importance, (3) novelty and insightfulness, (4) actability and guidance, and (5) effectiveness during evaluation (Iivari et al., 2021).

### 3.1.3 Echeloned Design Science Research

The echeloned Design Science Research (eDSR) methodology by Tuunanen et al. (2024) represents a recent addition to the set of DSR-related methods. More sequential approaches, such as the DSRM proposed by Peffers et al. (2007), have frequently been used and have demonstrated their value to researchers, but their application has revealed two main challenges. On the one hand, problems and objectives are difficult to define, as they often involve multiple perspectives on a complex issue. Moreover, problems are sometimes not well defined and may evolve over time. On the other hand, DSR projects often comprise multiple instantiations of an artifact, yet the handling and validation of these instantiations have not been adequately supported by existing DSR methods. To address these limitations, Tuunanen et al. (2024) introduced the eDSR methodology, which decomposes the traditional DSR phases into self-contained units that are easier to manage and report. These units are referred to as echelons, of which five design echelons are defined: (1) problem analysis, (2) objectives and requirements, (3) design and development, (4) demonstration, and (5) evaluation. Each design echelon is intended to make a distinct contribution to design knowledge. While each echelon is self-contained, they are also interrelated through one-to-many relationships.

The strength of eDSR lies in its ability to decompose DSR projects into smaller units, particularly in complex environments. This approach facilitates the reporting of complex problems and corresponding design objectives that would otherwise be difficult to capture using earlier DSR methods. As a result, intermediate artifacts can be presented, enabling more efficient reporting of DSR outputs. This also lowers the entry barrier for conducting DSR projects, as a complete DSR endeavor can be complex, lengthy, and difficult to publish. Moreover, other researchers can build upon intermediate artifacts to develop their own solutions, ultimately fostering a division of labor among researchers.

This approach was applied in paper **P9**, as it allowed us to focus on the complex problem of workarounds and their effects, as well as the objectives of a potential solution. Beyond providing methodological support during the research process, eDSR also enabled a more segmented publication strategy for the DSR project. This allowed us to emphasize the earlier stages of the DSR process, which are typically only briefly reported in traditional DSR studies.

## 3.2 Maturity Model Development

Maturity models represent a specific class of design artifacts that describe the staged development of a domain—such as processes, organizational capabilities, or information systems—along a structured evolution path (Becker et al., 2009). They provide criteria for assessing the current state of an object, assigning it to a maturity level, and deriving improvement measures. In IS research, maturity models are widely used to support positioning, benchmarking, and continuous improvement, particularly in IT management and digital transformation contexts.

Despite their popularity, maturity models have been criticized for limited methodological rigor and insufficient transparency in their development (Becker et al., 2009). Addressing this gap, Becker et al. (2009) conceptualize maturity models explicitly as DSR artifacts and derive a structured procedure model grounded in the Design Science Research paradigm (Hevner et al., 2004). Based on the DSR guidelines, they emphasize (1) justifying the need for a new model through comparison with existing approaches, (2) iterative development and evaluation, (3) a multi-methodological research design, and (4) comprehensive documentation of design decisions. Their procedure model spans problem definition, comparison of existing models, iterative design, transfer conception, and systematic evaluation.

More recent contributions further refine this perspective by structuring maturity model development around explicit design decisions. For example, Carvalho et al. (2019), building on Becker et al. (2009) and Mettler (2010), conceptualize development as a sequence of core activities—identifying the need, defining the scope, designing the model, evaluating it, and reflecting on its evolution. This decision-oriented view highlights that maturity model development is not a linear process but an iterative DSR endeavor requiring transparent justification of scope, maturity logic, and evaluation strategy.

In line with these principles, the maturity model developed in this dissertation **(P1)** follows a DSR-based, decision-oriented approach that integrates the procedural rigor proposed by Becker et al. (2009).

## 3.3 Case Studies

Case study research is a well-established research strategy for investigating contemporary phenomena in their real-world contexts, particularly when addressing how and why questions (Benbasat et al., 1987; Yin, 2017). It is especially appropriate when a phenomenon is complex, insufficiently understood, or inseparable from its contextual conditions (Dubé and Paré, 2003; Hartley, 2004). Rather than aiming for statistical generalization, case studies seek analytical generalization by developing or refining theoretical propositions based on rich, contextualized insights (Yin, 2017).

Depending on the unit of analysis and research objective, case studies can be designed as holistic or embedded and as single-case or multiple-case studies (Yin, 2017). Single-case designs are suitable for critical, unusual, common, revelatory, or longitudinal cases, while multiple-case designs follow a replication logic to enhance robustness and analytical validity (Cavaye, 1996; Yin, 2017). Case studies further differ in purpose as descriptive, explanatory, or exploratory, with exploratory designs being particularly useful for theory development in under-researched domains (Benbasat et al., 1987; Yin, 2017; Hartley, 2004).

A key strength of case study research lies in its use of multiple data sources, including interviews, observations, documents, archival records, and quantitative data, collected without experimental manipulation (Benbasat et al., 1987; Eisenhardt, 1989; Verleye, 2019). Data collection typically continues until theoretical saturation is reached (Glaser and Strauss, 1999), and triangulation across sources enhances construct validity and robustness (Yin, 2017). Case study research can follow either positivist–deductive or interpretive–inductive paradigms (Paré, 2004), with the latter emphasizing theory building through iterative analysis and systematic structuring of qualitative data (Klein and Myers, 1999; Gioia et al., 2013; Mayring, 2004).

Case studies were used across multiple contributions within this dissertation. In **P7** and **P8**, we conducted multiple-case studies (Yin, 2017) investigating three and four case organizations, respectively, to better understand how workarounds can be managed when they emerge and to examine when and how workarounds generate analyzable process data. Moreover, a single-case study **(P3)** was conducted at a German energy grid provider to understand how process mining projects evolve over time and which dynamics shape their development.

## 3.4 Systematic Literature Review

A systematic literature review (SLR) constitutes a fundamental research method in Information Systems (IS) research for identifying, analyzing, and synthesizing existing knowledge within a defined domain (Baker, 2000; Schryen et al., 2020). Unlike narrative reviews, an SLR follows a structured, transparent, and replicable process that ensures methodological rigor while supporting relevance through a clearly defined scope and critical engagement with prior work (vom Brocke et al., 2009). Literature reviews are particularly important in interdisciplinary research areas, where insights from multiple domains must be integrated to establish a comprehensive understanding of a phenomenon and to advance theory development (Webster and Watson, 2002).

Established IS guidelines propose a multi-stage review process that begins with defining the scope of the review, including its focus, goal, perspective, coverage, organization, and intended audience (H. M. Cooper, 1988). Relevant literature is then identified through systematic searches in leading journals, peer-reviewed conference proceedings, and academic databases using predefined search strings as well as inclusion and exclusion criteria (Okoli, 2015; Wolfswinkel et al., 2013). To enhance completeness, backward and forward searches are conducted by examining the references of identified studies and subsequent publications citing them (Levy and Ellis, 2006; Webster and Watson, 2002). The resulting body of literature is structured and synthesized using concept-centric techniques, such as concept matrices, which support the identification of patterns, inconsistencies, and research gaps (Webster and Watson, 2002; Schryen et al., 2020).

One established approach for conducting an SLR is the Preferred Reporting Items for Systematic Literature Reviews and Meta-Analyses (PRISMA) statement (Liberati et al., 2009). PRISMA provides a standardized framework for documenting the identification, screening, eligibility assessment, and inclusion of studies, thereby improving reproducibility and methodological transparency. Although originally developed for meta-analyses, PRISMA is increasingly applied to qualitative SLRs to systematically document the review process and enhance rigor. Within this dissertation, PRISMA was applied to conduct an SLR investigating the current body of literature on process mining and its application in real-world contexts **(P2)**.

## 3.5 Applied Research Process

This dissertation's research process is structured around two distinct yet closely related research contexts. The first context encompasses Research Objectives 1 and 2 and focuses on the organizational competencies required for successfully leveraging process mining, with particular attention to its application to KIPs. The second context addresses Research Objectives 3 and 4 and concentrates on the identification and management of workarounds through process mining. Each context comprises a set of interconnected research endeavors that mutually informed and influenced one another throughout the research process. Method wise, both contexts made heavy use of case study research (Yin, 2017) as well as a multitude of DSR related methods (Peffers et al., 2007; Becker et al., 2009; Sein et al., 2011; Tuunanen et al., 2024). An overview of the two research contexts and the research methods applied in each paper is provided in Figure 3.4.

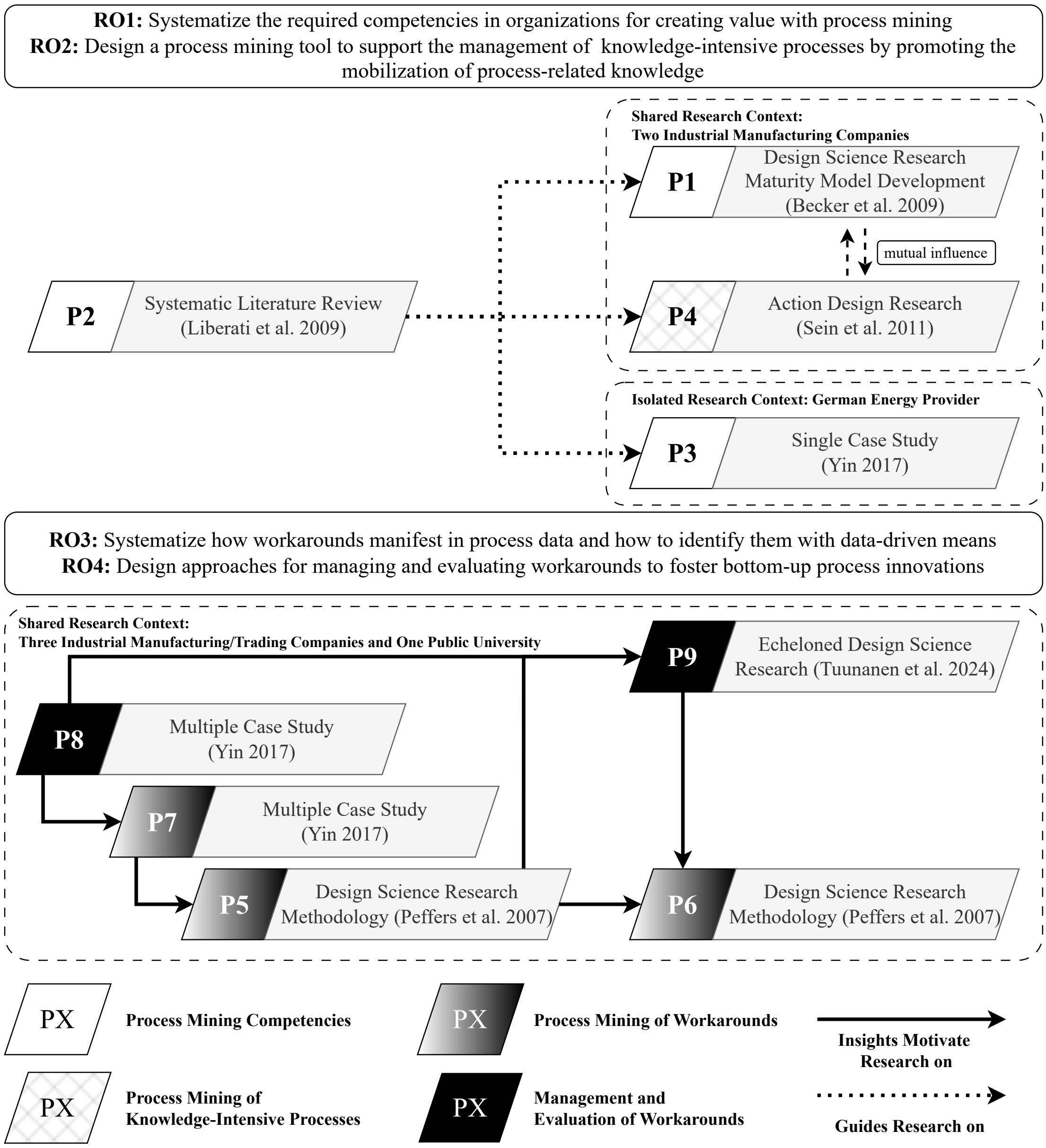


**Figure 3.4:** Research Design of this Dissertation

To address **research objective 1** (*to systematize the required competencies in organizations for creating value with process mining*), the dissertation first employed a systematic literature review on organizational uses of process mining **(P2)**. The review followed the Preferred Reporting Items for Systematic Literature Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009), which were considered particularly appropriate given the aim of synthesizing methodological insights rather than identifying entirely new research streams. In total, 28 peer-reviewed publications were included in the analysis. The findings indicate that prior research has largely focused on the design and refinement of technical artifacts, while methodological considerations regarding their organizational application and value contribution remain comparatively underdeveloped. Based on the structured synthesis of the literature, a set of research guidelines was derived to support more application-oriented and value-focused process mining research. These insights created a solid understanding on process mining and helped to steer our subsequent research, meaning we focused on the application of process mining in real-world contexts.

Therefore, subsequent research adopted a design-oriented perspective with regards to the organizational aspects of process mining adoption, which resulted in the development of a multi-factor maturity model aimed at assessing organizational readiness and capabilities for process mining **(P1)**. The maturity model was developed following the structured procedure proposed by Becker et al. (2009), which is grounded in the Design Science Research (DSR) paradigm (Hevner et al., 2004; Gregor and Hevner, 2013). This procedure comprised iterative development steps, including the identification of maturity dimensions, the definition of maturity levels, and the specification of assessment criteria. Empirical grounding was ensured through qualitative means such as workshops and interviews conducted as part of the assessment process, enabling contextualized maturity evaluations and the elicitation of underlying organizational rationales. Furthermore, semi-structured interviews were conducted with additional practitioners to derive concrete improvement measures, thereby explicitly linking maturity assessments to actionable organizational interventions.

Complementary to the qualitatively driven design approach with focus on process dynamics and how organization can better manage these with process mining, an in-depth single-case study was conducted (Yin, 2017). The study accompanied the introduction of a process mining tool at an energy provider and analyzed longitudinal system log data spanning a period of two years **(P3)**. Methodologically, the study combined qualitative case study principles with quantitative log analysis. By examining administrative and development-related events associated with the tool's implementation, recurring patterns and phenomena related to process change and process dynamics were identified. This approach enabled an empirical examination of how process mining itself introduces dynamics to an organization.

To further investigate the application of process mining in real-world contexts to fulfill **Research objective 2** (*design a process mining tool to support the management of* *knowledge-intensive processes by promoting the mobilization of process-related knowledge*) we leveraged ADR (Sein et al., 2011). The ADR study extended over a period of 39 months and involved two case organizations and one technology provider **(P4)**. and was structured into three major iterations, allowing for incremental refinement of the artifact and continuous empirical grounding. Intermediate and final results were reported across two publications, each corresponding to different stages of the ADR cycle.

**P4** and **P1** were conducted within the same overarching empirical context, as both studies were situated in the same publicly funded research project involving two industrial case organizations. As a result, the studies share a common empirical premise and exhibit mutual influence, particularly with regard to empirical insights and organizational understanding. Consistent with the ADR methodology, the focal study **(P4)** tightly integrated artifact development with organizational interventions and evaluation activities. Especially the close cooperation with the practitioners brought a relevant perspective into the development of the artifact. Evaluation activities comprised the application of the artifact in real organizational settings as well as formative assessments involving practitioners and researchers. In addition, the resulting design principles were evaluated with independent researchers and practitioners against established criteria for reusability (Iivari et al., 2021), thereby ensuring methodological rigor and relevance beyond the immediate empirical cases.

Taken together, the studies addressing **Research Objectives 1 and 2** form a coherent multi-method research program (Zachariadis et al., 2010) that combines literature synthesis, design-oriented research, and longitudinal empirical observation. The systematic literature review **(P2)** (Liberati et al., 2009) provided a conceptual foundation by identifying gaps in the organizational application of process mining and by deriving guidelines that informed subsequent empirical work. Building on these insights, the maturity model developed in **P1** (Becker et al., 2009) translated conceptual findings into a structured artifact for assessing organizational capabilities and readiness for process mining. In parallel, the longitudinal case study **(P3)** (Yin, 2017) provided empirical insights into the dynamics that arise when process mining technologies are introduced into organizational contexts, thereby complementing the design-oriented perspective with an observational one. Finally, the ADR study **(P4)** (Sein et al., 2011) operationalized these insights by designing and evaluating a process mining tool in close collaboration with practitioners, enabling the mobilization of process-related knowledge in knowledge-intensive processes. Together, these methods allowed the research within this context to iteratively move between theory building, artifact design, and empirical validation, thereby ensuring both conceptual rigor and practical relevance.

While the first context focuses on organizational capabilities for leveraging process mining, the second shifts the analytical perspective toward employee-driven process dynamics and the role of workarounds in shaping process behavior. Starting with **research objective 4** (*design approaches for managing and evaluating workarounds to foster bottom-up process innovations*), the research employed a multiple case study design (Yin, 2017) across three organizations **(P8)**. The study examined the lifecycle, evolution, and management of nine workarounds using multiple qualitative data sources, including document analysis, interviews, and workshops. Methodologically, the study emphasized triangulation across data sources to reconstruct how workarounds emerge, evolve, and are handled over time. The analysis resulted in the abstraction of a structured process model for managing workarounds, comprising four phases that collectively support the *discovery*, *explanation*, and *intervention* activities of the process science research framework. The resulting framework was validated with the participating organizations to assess its practical relevance. Further, it provided the foundation identifying relevant research avenues within this dissertation: one focusing on the data-driven identification of workarounds and another addressing the evaluation of workarounds and their organizational effects.

Addressing **research objective 3** (*to systematize how workarounds can be identified and analyzed*), the research adopted an exploratory and inductive approach to investigate how workarounds manifest in process data. Specifically, an inductive multiple case study design was employed (Yin, 2017) to examine mismatches between real-world process execution and recorded event data **(P7)**. The study involved the three case organizations from **P8** and one additional organization, resulting in the empirical analysis of 13 workarounds. Data collection and analysis focused on identifying recurring patterns through which workarounds affect the structure, semantics, and interpretation of process data. Based on cross-case comparison, workaround-induced mismatches were systematically categorized into three distinct types, yielding an empirically grounded classification of workaround effects on process data, thus building foundational knowledge relevant for identifying workarounds.

Building on this qualitative systematization, subsequent research focused on developing and evaluating data-driven approaches for the identification of workarounds. Methodologically, **P5** evaluated and extended the Semi-automated WORkaround

Detection (SWORD) framework (van der Waal, van de Weerd, et al., 2024). The research followed a design-oriented procedure (Peffers et al., 2007), conceptualized as an exaptation of an existing artifact (Gregor and Hevner, 2013). Empirical evaluation was conducted using event logs from two German manufacturing organizations, which also participated in **P7**. Through comparative case analysis, methodological limitations of the original framework were identified. These insights informed the systematic extension of the framework by introducing additional analytical steps and cross-case patterns, thereby broadening its analytical scope with respect to the *discovery* of workarounds. The extended framework was subsequently applied in both cases to validate its applicability in an industrial context.

The initial identification of workaround chains suggested that workarounds are more interconnected than initially assumed. This observation motivated further investigation while returning to **research objective 3**. To prepare a systematic evaluation of the organizational consequences of workarounds **(P9)**, the research adopted the recently proposed echeloned Design Science Research (eDSR) methodology (Tuunanen et al., 2024). This work focused on the first two echelons of eDSR, emphasizing problem formulation and initial validation. A detailed problem statement was developed based on rich field data from a medium-sized manufacturing organization and subsequently corroborated using empirical evidence from two additional organizations, consistent with the cases in **P7**. Based on this empirical grounding, a set of design objectives for methods aimed at evaluating workarounds was derived. Methodologically, this study establishes a foundation for future explanatory and design-oriented research on the broader organizational effects of workarounds.

Finally, to further extend the methodological scope of workaround identification, additional research explored the integration of workaround detection with Object-Centric Process Mining **(P6)**. This work followed an early-stage design science approach (Peffers et al., 2007), resulting in a preliminary conceptual design that combines control-flow–oriented and object-centric perspectives. The methodological focus lay on identifying and formalizing object-centric workaround patterns and adapting existing detection mechanisms to support the identification of interconnected workarounds and workaround chains. The resulting conceptual design provides a methodological foundation for future implementation and empirical evaluation by other researchers.

Taken together, the studies addressing **Research Objectives 3 and 4** follow an iterative research trajectory that combines qualitative theory building with design-oriented artifact development. The multiple case study in **P8** (Yin, 2017) established an initial understanding of how workarounds emerge, evolve, and are managed in organizations, resulting in a structured process model for workaround management. Building on this foundation, the multiple case study in **P7** (Yin, 2017) delved deeper and examined how workarounds manifest in process data, systematically categorizing the types of mismatches they create between real-world execution and recorded event data. These insights provided the empirical basis for subsequent design-oriented work. In particular, the DSR study in **P5** (Peffers et al., 2007) extended the SWORD framework to enable the semi-automated detection of workaround patterns in event logs, thereby translating qualitative insights into an operational analytical approach. Further, the problematization and design objectives in **P9** (Tuunanen et al., 2024) addressed the evaluation of workaround effects by formulating design objectives for systematic workaround assessment. Finally, the DSR study in **P6** (Peffers et al., 2007) expanded the methodological scope by exploring how workaround detection can be adapted to object-centric process mining settings, enabling the identification of interconnected workarounds across multiple process objects. Together, these studies progressively move from empirical understanding to analytical and design-oriented methods for identifying, analyzing, and evaluating workarounds using process mining.

# 4 Research Results

## 4.1 Synopsis of Findings

The contributions of this dissertation align with the core concern of recent process science research, which emphasizes understanding and managing process dynamics through BPM and related research disciplines (vom Brocke et al., 2024). Adopting the conceptual lens of process mining research—specifically with the aim of systematizing the organizational competencies required to create value from process mining—we investigate how process mining is currently applied in organizational settings from an Information Systems (IS) perspective. IS research is characterized by its dual mission of rigor and relevance (Hevner, 2007). However, despite the growing theoretical sophistication of process mining, there remains limited understanding of how its application translates into sustained business value in organizations (vom Brocke et al., 2021b). This gap results in an imbalance between rigor and relevance within the existing body of process mining research (Badakhshan et al., 2022; Grisold et al., 2020), a challenge that is also reflected in practice, where organizations frequently struggle to convert process mining insights into concrete actions (Martin et al., 2021).

Against the backdrop of the twofold mission of design-oriented IS research—namely, to develop type V theory for design and action while simultaneously addressing relevant business problems (Hevner et al., 2004; Gregor, 2006)—the limited and often unclear contextual usefulness of many proposed process mining artifacts emerges as a central weakness of the current knowledge base (Brennig, Löhr, et al., 2024, **P2**). This is particularly striking given that most of the reviewed studies explicitly or implicitly adopt the DSR paradigm, which is rooted in a pragmatic philosophy and places strong emphasis on practical consequences (Hevner, 2007).

In application-oriented research streams such as process mining, the systematic integration of the relevance cycle is therefore essential. To support researchers in more clearly articulating and strengthening the practical implications of their work, the findings of the systematic literature review were synthesized into four guidelines for conducting process mining research with enhanced relevance and managerial impact (see Table 4.1).

| Guideline | Scientific Implication | Managerial Implication |
|---|---|---|
| **Guideline 1**: Start with identifying a use case in a real-world organization. | Understand previous endeavors & assessment of whether specific solutions developed can be adapted or recombined in research projects. | Acquire insights into selecting and combining the application domain, process, and project goals to select a suitable process mining use case. |
| **Guideline 2**: Actively report on design objectives and decisions. | Understand how design decisions influenced the resulting artifacts, to enable a comparison with rival artifacts and approaches. | Make informed decisions regarding process mining techniques by aligning them with the specific design goals they aim to achieve. |
| **Guideline 3**: Evaluate artifacts with field data | Learn about evaluation techniques applicable to new research projects and gain understanding of design cycles in a paper. | Understand the data required to achieve the presented results to assess data availability and quality in their organizations. |
| **Guideline 4**: Discuss implications and quantify the business value. | Understand the business context and the usefulness or impracticality of specific process mining artifacts in organizations. | Learn the relation between process mining and business value, to better grasp the combination of different approaches to realize business value. |

**Table 4.1:** Guidelines for Researchers and Practitioners (Brennig, Löhr, et al., 2024)

First, process mining studies should begin with the identification of a clearly specified real-world use case. The SLR shows that many studies fail to explicitly link the research question, the selected process, and concrete project goals, or describe use cases only in abstract terms (Meyer et al., 2021; Pereira et al., 2020; Spagnolo et al., 2016). This lack of specificity complicates cross-study comparisons and limits the ability to assess whether proposed solutions are transferable to other organizational contexts (Badakhshan et al., 2022; van der Aalst, 2016). Clearly articulated use cases therefore provide an essential foundation for ensuring both contextual relevance and comparability across process mining studies.

Second, process mining research should explicitly report design objectives and key design decisions. The review reveals a systematic underreporting of design rationales, which obscures the relationship between the resulting IT artifact and the design process that produced it (Dumas et al., 2018; vom Brocke et al., 2021a). Transparent documentation of design objectives and decisions strengthens both the scientific interpretability of results and the practical reusability of artifacts in new contexts.

Third, developed artifacts should be evaluated using real-world field data, and the evaluation should be documented in sufficient detail. Although many studies claim to conduct case study evaluations, the SLR indicates that these evaluations are frequently reported only superficially, with limited information on data sources, evaluation procedures, or contextual conditions (Hevner et al., 2004; Hevner, 2007). Detailed reporting of evaluation settings and procedures is therefore essential for assessing whether an artifact meaningfully improves the target environment.

Fourth, process mining studies should explicitly discuss organizational implications and quantify business value where possible. The review reveals a persistent gap between analytical outputs and demonstrated organizational impact: results are often communicated within organizations but rarely translated into concrete actions or measurable value creation (Badakhshan et al., 2022; Syed, Leemans, et al., 2020). Consistent with a design science orientation, stronger emphasis on organizational consequences and realized actions is required (Sein et al., 2011; vom Brocke et al., 2021a; Grisold et al., 2020). Without such articulation, both researchers and practitioners lack reference points for assessing success and estimating the expected business value of future process mining projects.

With these insights and the guidelines at hand, we followed calls for actionable guidance to help organizations systematically assess and enhance their process mining readiness (Dunzer et al., 2021; Martin et al., 2021; Beverungen et al., 2021). We contribute to Research Objective 1 (RO1) by developing a Process Mining Maturity Model (P3M) (see Figure 4.1) that explains how organizations can systematically build the capabilities required for the sustainable adoption of process mining (Brock et al., 2024, **P1**). Although process mining has been widely recognized as a powerful approach for increasing process transparency and supporting evidence-based BPM (van der Aalst, 2016; Dumas et al., 2018; Grisold et al., 2020), many organizations struggle to move beyond isolated pilot projects and establish process mining as a recurring organizational capability (Martin et al., 2021; Dunzer et al., 2021). Existing research mainly discusses technical techniques or project-level success factors (Mans et al., 2013; Mamudu et al., 2022), leaving open how process mining capabilities can be systematically developed at the organizational level.

To address this gap, the paper introduces P3M, a multi-dimensional maturity model that conceptualizes process mining readiness as an organizational capability spanning five factors: *Organization*, *Data Foundation*, *Peoples' Knowledge*, *Scope of the Process Mining Activity*, and *Governance*. The model comprises 23 elements that capture essential capability areas for institutionalizing process mining, such as organizational embedding, process-oriented information systems, data accessibility, analytical competencies, and governance structures for data and processes. Conceptually, P3M

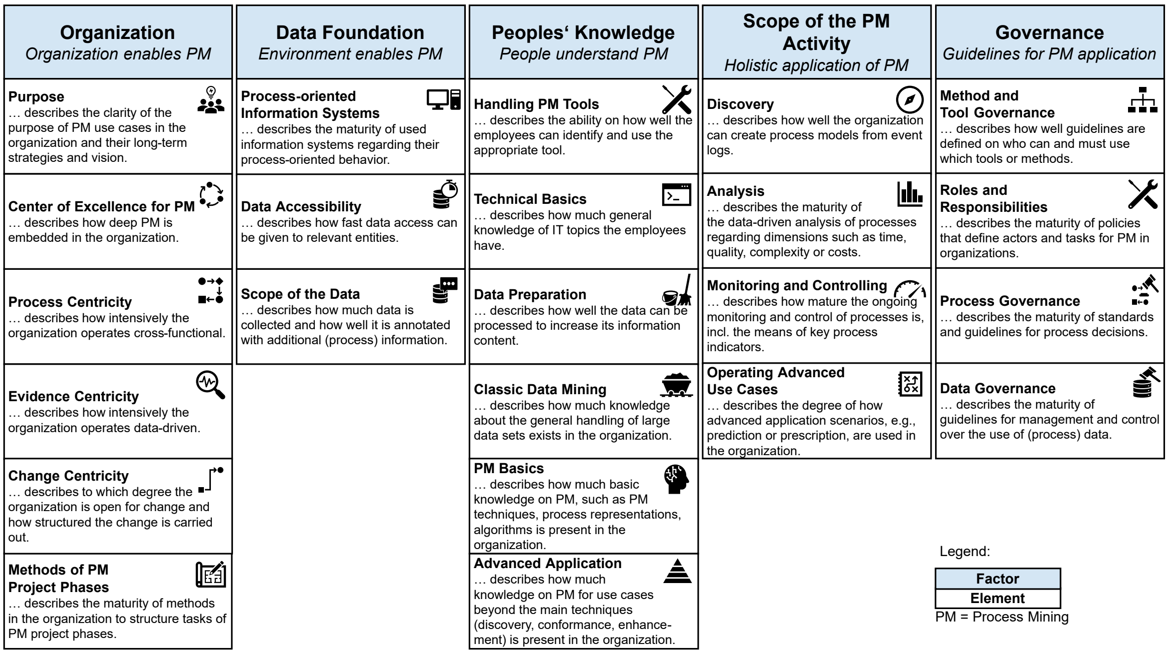


**Figure 4.1:** Overview of the Process Mining Maturity Model (P3M) (Brock et al., 2024)

builds on and adapts established BPM capability perspectives (Rosemann and De Bruin, 2005; Kerpedzhiev et al., 2021) and integrates process-mining-specific requirements related to event data infrastructures and analytical techniques (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016). Each element is structured along five maturity stages ranging from *Initial* to *Optimizing*, reflecting the evolutionary development of process mining initiatives from isolated experimentation toward systematic and strategically embedded use.

| | Factor | Action | Explanation |
|---|---|---|---|
| Organization | A-O1 | Raise awareness in management workshops | Let the top management experience process mining, e.g., by conducting a workshop where they mine an artificial process. |
| | A-O2 | Raise awareness in management circles | Present findings from process mining projects to the management. |
| | A-O3 | Anchor initiative centrally | One centralized initiative bundles all process mining activities within an organization. |
| | A-O4 | Anchor initiative in a hybrid setup | Connect a centralized initiative to multiple decentralized initiatives, e.g., in the corporate head quarters and branches. |
| | A-O5 | Human-centered communication campaign about processes and data | Highlight the importance of data and processes, e.g., by posting short videos on the intranet. |
| | A-O6 | Involve the IT department early | Communicate with the IT department early, and identify benefits for them. |
| | A-O7 | Combine the process mining initiative with larger digital transformation projects | Use larger digital transformation initiatives to validate and utilize process mining in an innovative environment. |
| Data Foundation | A-D1 | Implement a central data repository | Initialize a central data infrastructure, e.g., a data lake, to gather event data from different sources. |
| | A-D2 | Iteratively include new information systems | Do not try to include all information systems at once, but step-by-step. |
| | A-D3 | Implement the connectors to data sources | Utilize the connectors offered by process mining vendors to connect with the leading information system. |
| | A-D4 | Increase data quality with automation | Implement automation (e.g., RPA) to automatically maintain master data and increase data quality. |
| | A-D5 | Manually export first data for validation | Especially for on premise systems, using connectors is difficult. Manually export data for a low-effort start. |
| | A-D6 | Strive for perfection, deploy pragmatism | Most data can be used as is. Focus on that data to begin with. |
| Peoples' Knowledge | A-P1 | Determine an internal multiplier | Identify a person or group of persons to collect and share knowledge about process mining within the organization. |
| | A-P2 | Store knowledge in a wiki | Externalize knowledge by documenting it in a knowledge base. |
| | A-P3 | Train domain experts by involving them in the analysis | Train domain experts by including them in the data pre-processing and mining phases. |
| | A-P4 | Conduct trainings with vendors | Conduct the trainings of the respective process mining tool vendor. |
| | A-P5 | Specify trainings for the respective departments | Customize training to the specific needs of different departments (e.g., IT vs. business department). |
| | A-P6 | Utilize online-classes for self-study | Various online classes on process mining exist, where practitioners can train on particular aspects of process mining. |
| | A-P7 | Create a technical and a functional documentation | Create documentations for technical aspects and functional aspects, such as methods used or analysis steps taken. |
| Scope of the PM Activity | A-S1 | Systematically identify new use cases for your initiative | Determine use cases on the basis of benefits, interests, and data availability. |
| | A-S2 | Showcase previous use cases to gain attention of business units | Utilize regular meetings to demonstrate the possibilities of process mining to draw business attention. |
| | A-S3 | Start with process discovery | Start with process mining by applying process discovery, because it is the foundation for other techniques. |
| | A-S4 | Utilize classical data analytics techniques to gain general insights | Generate ordinary descriptive data analysis plots for domain experts. |
| | A-S5 | Gradually add new use cases to the initiative | Do not overload the organization with too many use cases, but work on them in a step-by-step fashion. |
| Governance | A-G1 | Create short-term data usage agreement | Create a written document in collaboration, e.g., with the works council, for conducting first PoC projects. |
| | A-G2 | Create long-term data usage agreement | Create a written document concerning multiple process mining projects, addressing data and privacy concerns. |
| | A-G3 | Involve the works council early | Involve the works council in the project to show that no individual performance is measured and jobs will not necessarily be rationalized. |
| | A-G4 | Develop a clear set of roles | Aside from classical roles such as process mining or domain expert, also consider roles such as an (analysis dashboard) user. |
| | A-G5 | Select the right process mining tool | Consider various aspects when selecting a vendor, and do not hesitate to test multiple vendors. |

**Table 4.2:** Identified Actions to Improve the Process Mining Maturity of Organizations. (Brock et al., 2024)

Beyond the maturity model itself, the paper derives 30 empirically grounded actions that organizations can implement to improve their process mining maturity (see Table 4.2). These actions translate abstract capability dimensions into concrete improvement measures, including anchoring process mining initiatives organizationally (Reinkemeyer et al., 2022), establishing reliable event data infrastructures (Pingos and Andreou, 2022), building analytical competencies among process participants (van der Aalst, 2016), systematically expanding use cases (Eggers et al., 2021), and defining governance structures for data access and roles (Kipping et al., 2022; van Eck et al., 2015). Together, these actions provide actionable guidance for overcoming the frequently observed intention–action gap in process mining initiatives.

In alignment with RO1, this paper therefore contributes both a structured maturity framework and a set of practical improvement actions that support organizations in systematically developing process mining capabilities and embedding data-driven BPM practices in increasingly dynamic process environments.

As elaborated, turning process mining projects into actual value is a challenging task (Badakhshan et al., 2022; Martin et al., 2021). The contribution of the third paper (Skolik and Löhr, 2026, **P3**) aligns with the growing body of process science research that emphasizes understanding and managing process dynamics through BPM and process mining (vom Brocke et al., 2024). While prior work has extensively demonstrated how process mining enables transparency in business processes and supports data-driven process improvement (van der Aalst, 2016; Reinkemeyer, 2020a), existing research predominantly focuses on the dynamics of the analyzed processes themselves. In contrast, the dynamics of process mining projects as sociotechnical endeavors—including their development, adoption, and evolution over time—remain largely unexplored. From an IS perspective, this represents a critical blind spot, as process mining projects constitute complex interventions that actively shape organizational routines, decision-making, and BPM initiatives (Pentland, Liu, et al., 2020; Grisold et al., 2021).

Addressing this gap, the investigation of the internal dynamics of a long-running process mining introduction project provides a novel analytical lens: the quantitative analysis of system log data generated by the process mining platform itself (Skolik and Löhr, 2026). To the best of our knowledge, such platform-internal logs have not yet been systematically analyzed to study the progression, challenges, and success factors of process mining projects. Existing studies primarily rely on qualitative accounts, post-hoc evaluations, or outcome-oriented success factors (Mans et al., 2013; Mamudu et al., 2022), which limits the ability to identify early warning signals and objective indicators of project dynamics. Consequently, although success and failure factors of process mining initiatives are discussed in the literature, quantitative evidence capturing how these factors unfold over time remains largely missing.

| Finding/ Phenomenon | Description | Effect on Process Dynamics |
|---|---|---|
| Two Development Phases | A development and productive system development approach allows to develop intermediate solutions | Rapid process advancements through intermediate solutions |
| Technical Debt | Maintenance of a process mining project slowly becomes more important, happens frequently | Process Drift - focus shifts from development to maintenance |
| Scope and Feature Creep | An over proportional influx in feature updates points to scope and feature creep and takes development time away from main projects | Diminishing returns for the process, yet rising development efforts |
| Sufficient User Base | Establish a proper user base for each phase | Successful implementation into the process |

**Table 4.3:** Recurring and Interrelated Phenomena of a Process Mining Project (Skolik and Löhr, 2026)

The study reveals four recurring and interrelated phenomena that significantly shape the trajectory and outcomes of a process mining project (see Table 4.3). First, the separation of development and productive environments into two distinct development phases enables iterative, data-driven process improvements and fosters early user involvement, which also several practitioners confirmed as a suitable action for increasing process mining maturity (Brock et al., 2024). Second, the accumulation of maintenance activities highlights the emergence of technical debt (Martini and Bosch, 2015) which, if left unmanaged, can induce process drift (Pentland, Liu, et al., 2020) and undermine previously achieved improvements. Third, the analysis uncovers scope and feature creep as quantitatively observable patterns in platform logs, showing how incremental feature requests can gradually divert resources away from high-impact initiatives. Fourth, the findings demonstrate that establishing and sustaining a sufficient user base throughout different project phases is crucial for adoption and enables bottom-up process change once users internalize the capabilities of process mining (Brock et al., 2024).

By conceptualizing these phenomena and linking them to observable indicators in system log data, we could provide two central contributions. From a scientific perspective, it extends process mining and BPM research by shifting attention from outcome-centric evaluations toward the dynamic inner workings of process mining projects, thereby enriching the understanding of process mining as a socio-technical intervention (Mahringer and Walleser, 2023). From a practical perspective, the identified patterns provide practitioners with actionable insights and early warning signals that can be used to proactively steer process mining initiatives, mitigate risks such as technical debt and scope creep, and strengthen long-term value creation. In doing so, the paper lays the groundwork for future research on longitudinal, data-driven assessments of process mining maturity and project success.

We have shown that process mining is a tool that helps to understand general dynamics within an organization (Brock et al., 2024) but also introduces dynamics of its own (Skolik and Löhr, 2026). The contribution of the focal paper (Brennig et al., 2026, **P4**) directly addresses Research Objective 2 (RO2) of this dissertation, which focuses on developing design knowledge that enables organizations to systematically apply process mining to knowledge-intensive processes (KIPs). Existing BPM systems and conventional process mining approaches provide limited support for these processes, as they are primarily designed for standardized, predictable, and highly digitalized operational processes (van der Aalst, 2016; van der Aalst and Carmona, 2022). This mismatch results in fragmented knowledge bases, limited reuse of experiential insights, and persistent challenges in managing KIPs systematically (Ramesh and Tiwana, 1999).

From a process science and Information Systems perspective, this gap reflects a broader limitation of current process mining research: while it has matured considerably in terms of analytical rigor, its applicability to strategically relevant, human-centered processes remains underdeveloped. In particular, three challenges impede the use of process mining for KIPs. First, process mining primarily analyzes explicit process-related knowledge captured in event logs, whereas KIPs depend strongly on tacit knowledge that is shared through experience and social interaction (Nonaka and Takeuchi, 1995; Di Ciccio et al., 2015). Second, deviations in KIPs are often intentional and value-creating, yet traditional process mining approaches interpret deviations mainly through a compliance-oriented lens (Eppler et al., 1999; Isik et al., 2012). Third, process mining predominantly supports retrospective analysis at the process type level, whereas KIPs require run-time support to inform context-sensitive decision-making in individual process instances (Di Ciccio et al., 2015; de Almeida Rodrigues Gonçalves et al., 2023). Together, these limitations hinder the creation of business value from process mining in knowledge-intensive contexts and motivate the need for new design-oriented guidance.

To address RO2, this paper develops a type V theory for design and action (Gregor, 2006), articulated as five theory-ingrained design principles (Gregor et al., 2020), for a new class of IT artifacts coined "*process mining of knowledge-intensive processes*" (see Table 4.4). The design principles are grounded in the theory of organizational knowledge creation, using the SECI model (Nonaka and Takeuchi, 1995) as a kernel theory.

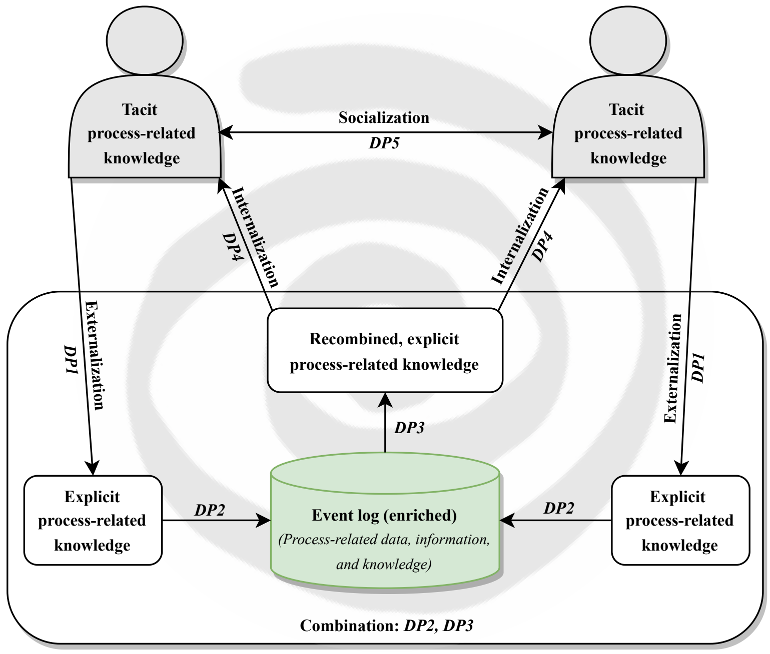


**Figure 4.2:** Conceptual Link between SECI Model and Design Principles for Process Mining of KIPs (Brennig et al., 2026)

By systematically operationalizing the SECI modes—socialization, externalization, combination, and internalization—the paper specifies how process mining can be extended to mobilize tacit process-related knowledge, integrate richer contextual information into event logs, and support learning from similar process instances at run time (see Figure 4.2).

DP1 advocates the systematic externalization of tacit process-related knowledge into shareable representations such as text, images, or other digital artifacts. By making implicit knowledge explicit, it becomes accessible for others to reuse, extend, and recombine. While many organizations acknowledge the importance of capturing such knowledge, they often lack structured mechanisms to translate tacit insights into explicit, process-related information. Building on this foundation, DP2 emphasizes the enrichment of event logs with categorized and structured information. To ensure both machine readability and human interpretability, additional attributes must be defined and systematically organized, thereby extending traditional event logs beyond their standard parameters. This structured augmentation enables more comprehensive analysis and integration of process-related knowledge.

DP3 focuses on the systematic retrieval and analysis of this enriched data through process mining. Leveraging process mining techniques reduces biases associated with subjective human recall and supports more objective performance assessment. To fully exploit the potential of enriched event logs, process mining capabilities should be expanded to incorporate unstructured data through technologies such as natural language processing and computer vision. Moreover, predictive and action-oriented analytics are required to inform decision-making and actively support process execution. Complementing this analytical perspective, DP4 proposes the internalization of processed information by delivering context-sensitive insights directly to process participants. By providing relevant information at the point of action, individuals can generate new process-related knowledge, enhance their performance, and make informed decisions, particularly in KIPs. Finally, DP5 suggests leveraging process mining to identify and connect knowledge carriers within the organization. Through drill-down mechanisms, knowledge contributions can be traced back to their original sources. As knowledge entries are stored, transformed, and recombined within the artifact, they remain accessible for future retrieval and reuse, thereby fostering organizational learning and collaboration.

Theoretically, Research Objective 2 reconceptualizes process mining for knowledge-intensive processes (KIPs) by grounding it in organizational knowledge creation theory, particularly the SECI model (Nonaka and Takeuchi, 1995). It shows how knowledge management capabilities can extend traditional, data-centric process mining approaches by systematically externalizing tacit process-related knowledge and embedding it into enriched event logs. In doing so, process mining is reframed as a mechanism that supports continuous cycles of knowledge creation, enabling knowledge to evolve from individual instances to higher organizational levels and making tacit process-related knowledge analytically accessible.

From a practical perspective, the derived design principles provide actionable guidance for transforming tacit and embedded process-related knowledge into explicit, structured, and analyzable formats. They demonstrate how event logs can be expanded to capture knowledge elements that are typically excluded from analysis, thereby establishing a foundational knowledge base for KIPs. This supports more informed and objective decision-making, fosters knowledge sharing among process participants, and enables the ongoing adaptation and improvement of knowledge-intensive processes. Collectively, these contributions establish a foundational design knowledge base for process mining of KIPs and provide a key building block for the dissertation's overarching goal of enabling value creation from process mining in complex, dynamic organizational contexts.

| | |
|---|---|
| **Design principle 1 (externalization): Externalize tacit process-related knowledge as information** | |
| Implementer | Process participant |
| User | IT artifact & process analyst |
| Aim | To externalize a process participant's tacit knowledge related to the KIP and add it as unstructured information to the artifact. |
| Mechanism | The artifact should incorporate an input mask that enables process participants to externalize process-related knowledge in textual or attached form, including knowledge that exists but has not yet been shared within the organization. Through a dedicated selection function, each contribution can be associated with the corresponding process instance and activity, ensuring that the unstructured information is properly contextualized and retrievable for process mining analysis. |
| Rationale | The externalization of tacit knowledge, as described in the SECI model, is crucial for sharing and building new knowledge (Nonaka and Takeuchi, 1995), especially in knowledge-intensive processes reliant on skilled participants (Di Ciccio et al., 2015; Isik et al., 2012; Eppler et al., 1999; Gronau and Weber, 2004). However, many organizations lack effective mechanisms to convert tacit process-related knowledge into explicit, shareable information. |
| **Design principle 2 (combination): Enhance event log with new attributes to categorize information** | |
| Implementer | IT artifact & process analyst |
| User | IT artifact & process analyst |
| Aim | To categorize and classify information and store it as data in the event log related to a specific process instance. |
| Mechanism | Transform the information into data by categorizing and assigning it as attributes to the event log, ensuring both machine-readability and human interpretability. |
| Rationale | Unstructured data are challenging to analyze efficiently and are often excluded from event logs, limiting their potential for contextual insights (Pentland, Recker, et al., 2020). Additionally, while algorithms can find correlations in unstructured data, their lack of explainability hinders their use in making decisions that require interpretation and rationale. |
| **Design principle 3 (combination): Retrieve information from the event log through process mining** | |
| Implementer | IT artifact & process analyst |
| User | Process participant |
| Aim | To (re-)combine data into information by retrieving information on past process instances from the event log. |
| Mechanism | Identify similar past process instances (e.g., through trace clustering (M. Song et al., 2009)). Extend and implement process mining techniques (especially predictive and action-oriented techniques) to support process participants. State the effect of the actions taken based on the provided information and integrate a feedback loop so that the system can learn further. |
| Rationale | Decision-making and performance in knowledge-intensive activities are influenced by availability heuristics, where the subjective recall of past events biases judgment (Tversky and Kahneman, 1973). Combining explicit knowledge from diverse sources is essential (Nonaka and Takeuchi, 1995; Nonaka et al., 2000), as even experienced participants struggle to overcome these biases when recalling similar past events. |
| **Design principle 4 (internalization): Internalize information to create new process-related knowledge** | |
| Implementer | IT artifact & process analyst |
| User | Process participant |
| Aim | To enable process participants to internalize information and create new process-related knowledge. |
| Mechanism | Present process participants with relevant process-related information that is useful to their specific context and situation. |
| Rationale | Knowledge is created through internalization, where individuals relate information to their experiences and beliefs (Nonaka and Takeuchi, 1995; Nonaka et al., 2000). Our study found that the information presented to process participants during tasks significantly influences their performance in business processes. |
| **Design principle 5 (socialization): Identify and network knowledge bearers through process mining** | |
| Implementer | IT artifact & process analyst |
| User | Process participant |
| Aim | To identify knowledge bearers and connect them. |
| Mechanism | Use previously added and recombined information to reverse engineer the knowledge transformation process and trace back the knowledge to the original contributor. |
| Rationale | Individual knowledge contributes to the organizational knowledge base only when shared (Bhatt, 2000; Nonaka and Takeuchi, 1995; Nonaka et al., 2000), yet knowledge bearers often remain hidden and difficult to identify. Our study found that experienced process participants with valuable knowledge from similar past instances were frequently unknown and inaccessible to others. |

**Table 4.4:** Design principles for Process Mining of KIPs (Brennig et al., 2026)

We demonstrated how process mining can be applied in environments characterized by intended dynamic behavior, such as KIPs, but process dynamics can emerge from many sources. One such source is workarounds, for which data-driven approaches such as process mining have proven effective in revealing workaround behavior within data traces (van der Waal, van de Weerd, et al., 2024). However, workarounds do not only comprise properly recorded behavior. Understanding how workarounds manifest in event data—and how they may remain invisible in such data—was therefore essential for further advancing data-driven approaches to workaround identification.

We contribute to Research Objective 3 (RO3) by establishing the conceptual foundations and boundary conditions for identifying workarounds with process mining (Bartelheimer et al., 2025, **P7**). Process mining relies on the premise that event data accurately reflect real-world process execution (IEEE Task Force on Process Mining, 2012). However, mismatches between process models, event data, and actual execution are common in practice and have largely been treated as data quality issues or noise (Buijs et al., 2014; Rogge-Solti et al., 2016). By adopting workarounds as a theoretical lens, this paper reframes such mismatches as informative signals of employee-induced process dynamics rather than mere deficiencies in logging infrastructures.

Based on an inductive multiple case study of 13 workarounds across four heterogeneous organizations, the paper develops a systematic classification of workaround-related mismatches between process models, event data, and real-world execution. Three distinct categories are identified: *phantom workarounds*, *transparent workarounds*, and *offline workarounds* (see Figure 4.3). These categories differ fundamentally with respect to their visibility in event data and, consequently, their detectability through process mining techniques.

From the perspective of RO3, this distinction is critical. The study shows that only transparent workarounds—i.e., deviations that are both executed and faithfully recorded in event data—can be reliably identified using data-driven approaches such as process mining and pattern-based workaround detection frameworks (e.g., SWORD). Phantom workarounds, which leave misleading or fictitious traces in event data, and offline workarounds, which are executed without any digital trace, systematically evade or distort purely data-driven detection. As a result, process mining may either falsely suggest the existence of workarounds without revealing their actual nature or fail to detect them altogether.

This paper thus provides the necessary conceptual groundwork for data-driven workaround detection. It delineates the subset of workarounds that can be iden-

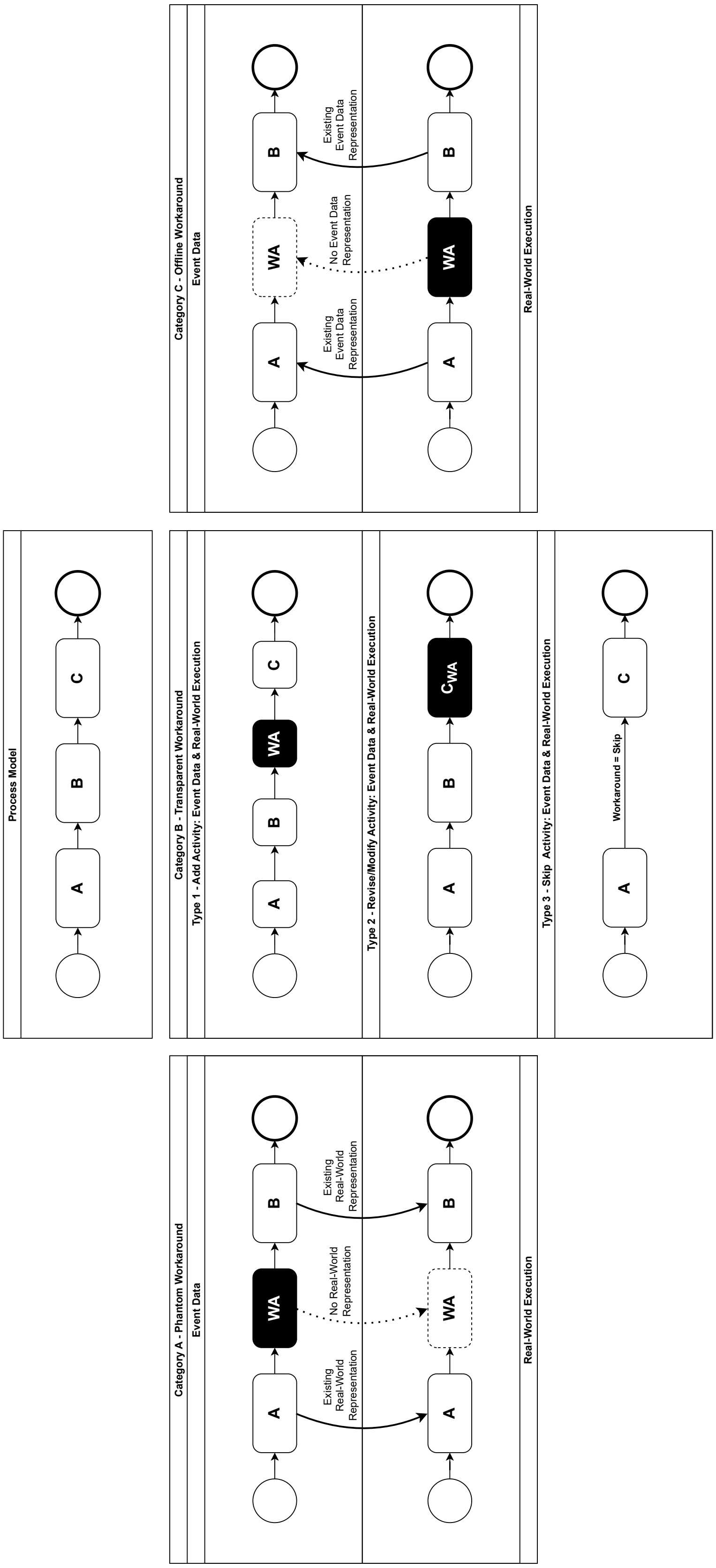


**Figure 4.3:** Workaround-Related Mismatch Categories (Bartelheimer et al., 2025)

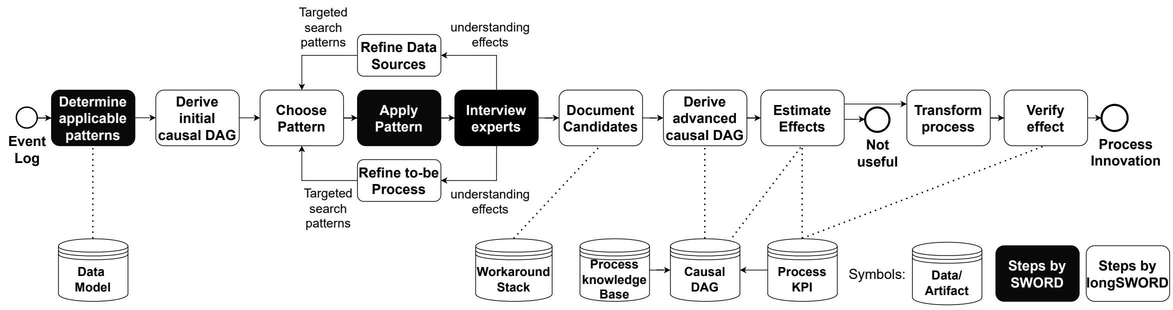


**Figure 4.4:** The LongSWORD Method and Key Artifacts (Löhr et al., 2025)

tified through process mining, highlights the risks of misinterpretation when event data are taken at face value (Andrews, Suriadi, Ouyang, et al., 2018), and underscores the need to combine quantitative detection with qualitative inquiry. By positioning workarounds as a key source of observable and unobservable mismatches, the study strengthens the theoretical validity of workaround mining and informs the responsible use of process mining for analyzing bottom-up, employee-induced process dynamics.

Taking a closer look at the category of transparent workarounds, we focused on improving existing data-driven approaches, particularly the SWORD framework (van der Waal, van de Weerd, et al., 2024). From the perspective of RO3, however, SWORD exhibits three key limitations: it has primarily been validated in highly standardized domains, provides limited guidance on data preparation and iterative refinement, and focuses on identifying workaround candidates at the level of individual process instances, largely neglecting cross-case and organizational effects.

To address these limitations, this paper follows an exaptation strategy (Gregor and Hevner, 2013) and develops LongSWORD (Löhr et al., 2025, **P5**), an enhanced workaround detection method tailored to industrial contexts (see Figure 4.4). Using a Design Science Research methodology (Peffers et al., 2007), the approach was developed and evaluated in two manufacturing organizations. The method extends SWORD both by augmenting the pattern set and by reframing the detection process as iterative and context-sensitive.

A central contribution of LongSWORD is the introduction of two additional cross-case patterns. Pattern 23 (workaround chains) enables the identification of interdependent workarounds, acknowledging that individual adaptations may trigger further workarounds by creating new misfits elsewhere in the process. Pattern 24 (drift of process KPI) addresses situations in which a workaround becomes dominant over time and replaces the intended process execution, thereby becoming invisible to variance-based detection. By incorporating drift analysis at the process level (Sato et al., 2021), this pattern enables the detection of gradual normalization and structural change induced by workarounds.

Beyond extending the pattern set, LongSWORD enhances the SWORD method across its application lifecycle. Before pattern execution, it emphasizes iterative alignment between event logs, reference process models, and organizational routines. During analysis, workaround detection is treated as an iterative learning process in which findings inform refinements of data and process models. After detection, LongSWORD supports the systematic interpretation of workarounds and their implications through causal-directed acyclic graphs (Pearl, 1995), enabling analysts to reason about trade-offs such as short-term effectiveness versus long-term process debt (Martini et al., 2020).

This paper contributes a reusable, data-driven method for identifying and analyzing workarounds in industrial core processes. By extending pattern-based detection with cross-case analysis, iterative refinement, and causal reasoning, LongSWORD conceptualizes workarounds not merely as deviations but as analytically accessible signals of misfit, risk, and innovation potential, thereby laying the foundation for subsequent research on the systematic management of workarounds.

Contributing further to Research Objective 3 (RO3) by advancing the data-driven identification and analysis of workarounds, I focus particularly on the interdependencies between workarounds that span multiple process instances or object types, also called workaround chains (Löhr, 2026, **P6**). While prior research has established that workarounds are purposeful deviations enacted to overcome organizational or technical misfits (Alter, 2014; Bartelheimer et al., 2023), most existing approaches—including qualitative methods and case-centric process mining techniques—treat workarounds as isolated phenomena. Our own empirical findings, however, indicate that workarounds are often interconnected, forming workaround chains in which one adaptation triggers subsequent ones across cases or even across processes (Löhr et al., 2025; Bartelheimer et al., 2025; Reineke et al., 2026). Systematically identifying such chains remains a challenging task.

State-of-the-art data-driven workaround detection approaches, most notably the SWORD framework (van der Waal, van de Weerd, et al., 2024), are grounded in a

| | Workaround detection patterns | Activity | Time |
|---|---|---|---|
| **Control-flow** | C1 - *Occurrence of activity | Specific | |
| | C2 - Occurrence of recurrent activity sequence | High quality | Low quality |
| | C3 - Activity frequency out of bounds | High quality | |
| | *C4 - *Occurrence of activities in an order different from process model* | *Specific* + ***object-centric process model*** | *Low quality* |
| | *C5 - *Occurrence of mutually exclusive activities* | *Specific* + ***object-centric process model*** | - |
| | *C6 - *Occurrence of unusual neighboring activities* | *Specific* + ***object-centric process model*** | *Low quality* |
| | C7 - Occurrence of directly repeating activity | High quality | Low quality |
| | *C8 - *Missing occurrence of activity* | *Specific* | - |
| **Object-centric** | O1 - Occurrence of an unusual number of different object types | High quality | - |
| | O2 - Occurrence of an unusual number of objects of the same type | High quality | - |
| | *O3 - *Involvement of unintended object types* | *Specific* + ***object-centric process model*** | - |
| | *O4 - *Unintended flow between object types* | *Specific* + ***object-centric process model*** | *Low quality* |
| | *O5 - *Occurrence of mutually exclusive objects* | *Specific* + ***object-centric process model*** | - |

Those marked with * can only be leveraged with extended domain knowledge or on known workaround types.

**Table 4.5:** Updated Control-Flow and New Object-Centric Patterns for Identifying Workarounds (Löhr, 2026)

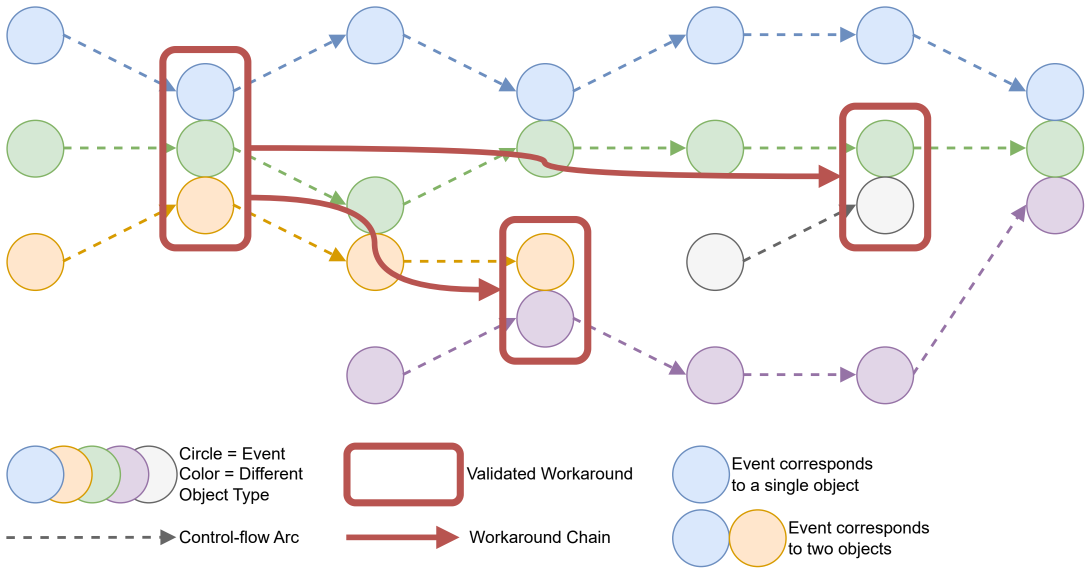


**Figure 4.5:** Visualization of the Results of the ChainSWORD (Löhr, 2026)

case-centric event log perspective. While this perspective is well suited for identifying deviations within individual process instances, it limits the ability to analyze cross-case dependencies and interactions between multiple business objects. We introduced initial extensions toward cross-case identification with LongSWORD (Löhr et al., 2025), which conceptualizes workaround chains and process KPI drift as analytical patterns. However, these extensions did not operationalize the detection of workaround chains in a systematic and quantitative manner.

To address this gap, this paper introduces ChainSWORD (Löhr, 2026), a research-in-progress artifact that elevates the SWORD framework from a case-centric to an object-centric process mining (OCPM) perspective (van der Aalst, 2019). Following a Design Science Research approach (Peffers et al., 2007), ChainSWORD adapts existing SWORD patterns and introduces five novel object-centric patterns that leverage interactions between multiple object types captured in object-centric event logs. By abandoning the single-case assumption and incorporating an advanced object-centric case notion (van Detten et al., 2025), ChainSWORD enables the identification of workaround candidates that manifest through unusual object interactions, unintended object flows, or abnormal object cardinalities—phenomena that remain invisible in traditional event logs (see Table 4.5).

Beyond extending the pattern set, ChainSWORD contributes a methodological procedure for identifying potential workaround chains. Individual workaround candidates detected at the object level are linked through paths in the object-centric event graph, allowing analysts to identify temporal and structural dependencies between workarounds across objects, cases, and processes (see Figure 4.5). This shifts the analytical focus from isolated deviations toward networks of adaptations, providing a first quantitative foundation for analyzing how local problem-solving behavior can propagate through organizational processes.

In alignment with Research Objective 3, this paper contributes a conceptual and methodological extension of data-driven workaround detection that explicitly addresses cross-case and cross-process interdependencies. While ChainSWORD is presented as a research-in-progress artifact and has not yet been fully implemented or evaluated, it establishes a theoretically grounded and technically plausible approach for identifying workaround chains using object-centric process mining. In doing so, it complements and deepens the contributions of LongSWORD by providing the analytical mechanisms required to operationalize workaround chains, thereby further strengthening the empirical and methodological basis for understanding workarounds as systemic phenomena rather than isolated deviations.

While prior research has established that workarounds are widespread, goal-directed deviations enacted by process participants to overcome misfits (Alter, 2014; Bartelheimer et al., 2023), organizations have struggled to systematically leverage these deviations for sustainable process improvement. As a result, workarounds are frequently tolerated as temporary fixes or suppressed as undesirable deviations rather than being treated as valuable inputs for organizational learning and innovation.

Addressing this gap, we investigated how workarounds can function as catalysts for process innovation and why organizations often fail to realize this potential (Assbrock et al., 2024, **P8**). This paper contributes to Research Objective 4 (RO4) by explaining how organizations can purposefully manage workarounds and transform them into bottom-up process innovation. Drawing on a multiple case study of nine workarounds across three organizations, the study examines how individual workaround initiatives either (a) remain isolated at the task level, (b) diffuse informally without organizational action, or (c) are successfully translated into formal process innovation. In doing so, the paper shifts the analytical focus from why workarounds emerge to how organizations respond to them.

From a theoretical perspective, the paper contributes a process-oriented explanation of the workaround-to-innovation transition. Building on the BPM lifecycle (Dumas et al., 2018) and organizational learning theory (SECI) (Nonaka and Takeuchi, 1995), it conceptualizes the transformation of workarounds into process innovation as a four-phase organizational process comprising the following phases: *"Identify & Share"*, *"Categorize & Analyze"*, *"Evaluate & Decide"*, and *"Implement & Transform"*. The findings show that workarounds do not automatically result in innovation; instead, innovation depends on whether organizations establish appropriate governance structures, communication mechanisms, and decision protocols.

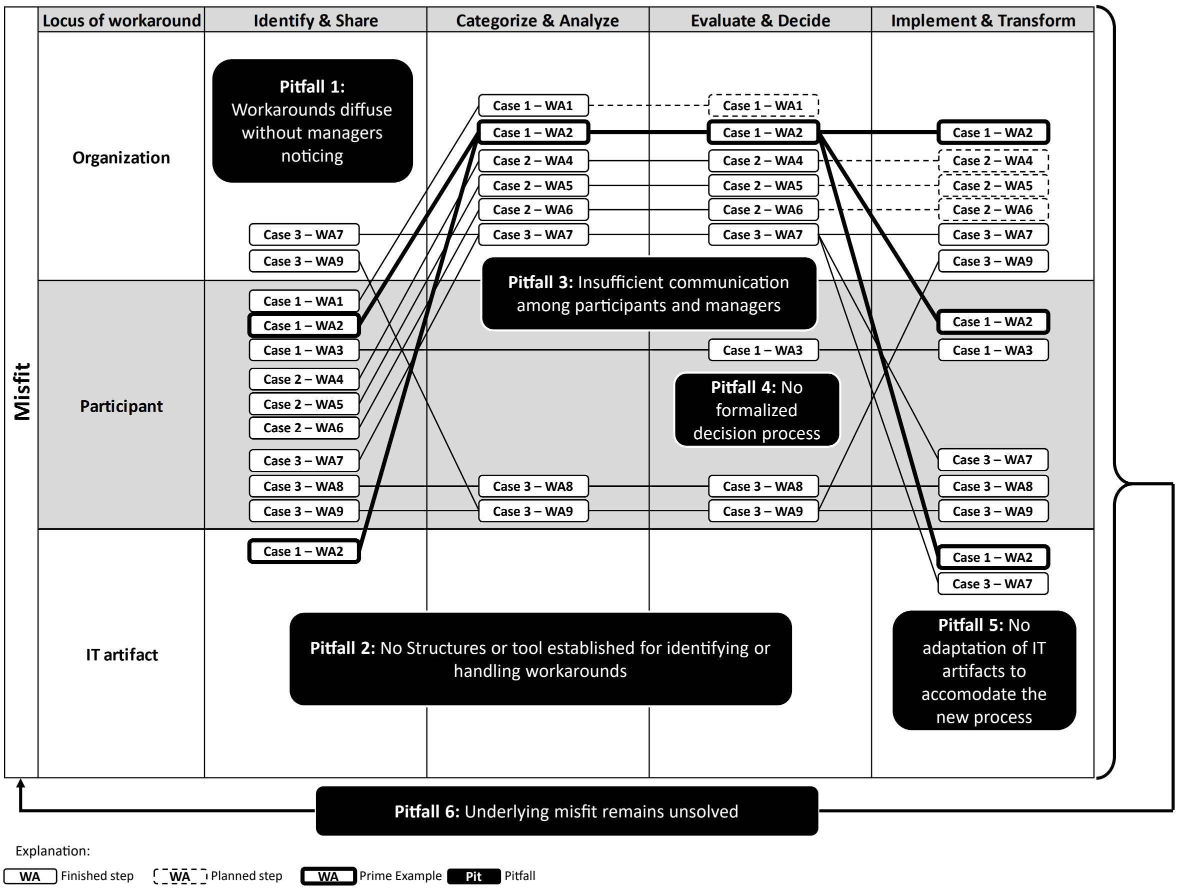


**Figure 4.6:** Workaround-to-Innovation Process and Potential Pitfalls (Assbrock et al., 2024)

A key contribution to RO4 is the identification of six recurring pitfalls that prevent organizations from leveraging workarounds for process innovation (see Figure 4.6). Workarounds frequently diffuse informally among employees without managerial awareness, often spreading through direct communication before being recognized at the organizational level. Because management attention is a prerequisite for formal process redesign or IT adaptation (Bartelheimer et al., 2023), the absence of systematic monitoring mechanisms delays corrective action and increases the risk of process drift. At the same time, many organizations lack structured governance mechanisms to identify, evaluate, and manage workarounds in a standardized manner. Although workarounds are commonplace (Li et al., 2017), formalized end-to-end processes that transform them into innovations are often missing. Implementing a workaround-to-innovation process (Beverungen et al., 2024), supported by ambidextrous capabilities (O'Reilly and Tushman, 2004), would enable organizations to systematically leverage recurring deviations—conceptualized as "workaround stacks" (Bartelheimer et al., 2023)—for continuous improvement.

Furthermore, communication between process participants and managers is frequently informal or incomplete, hindering timely escalation and shared understanding (Bartelheimer et al., 2023). Decision-making about workarounds tends to be ad hoc and lacks transparent evaluation criteria, resulting in inconsistent or delayed resolutions (Alter, 2014). In addition, IT artifacts are rarely adapted to accommodate modified processes, leaving known misfits unresolved and reinforcing manual fixes (Bartelheimer et al., 2023). Consequently, workarounds are often tolerated as long-term solutions, allowing underlying misfits to persist and accumulate over time (Koopman and Hoffman, 2003). Adopting a holistic perspective on interrelated misfits and workaround stacks can therefore serve as a trigger for broader process redesign and structural transformation initiatives (Bartelheimer et al., 2023).

From a managerial perspective, the paper offers concrete guidance for organizations operating in volatile environments where traditional top-down BPM approaches are insufficient on their own. It demonstrates how managers can move beyond merely tolerating or suppressing workarounds and instead actively orchestrate their evaluation and transformation into process innovations. By doing so, organizations can increase their adaptive capacity, respond more quickly to emerging challenges, and mitigate the negative side effects of unmanaged workarounds, such as process drift (Bose et al., 2014), data quality issues (Bartelheimer et al., 2025), or compliance risks (Carmona et al., 2022).

In alignment with Research Objective 4, this paper thus provides a structured understanding of how workarounds can be governed, evaluated, and institutionalized as part of dynamic process innovation. It positions workarounds not as isolated deviations but as strategically relevant signals of misfit and opportunity, offering a comprehensive framework for managing the interplay between individual adaptation, organizational decision-making, and sustained process change.

While the contributions to RO3 constitute a toolset for the first phase of the workaround-to-innovation process, we continued to further develop methods appropriate for evaluating workarounds. We contribute to RO4 by addressing how organizations can systematically evaluate workarounds to support informed managerial decision-making (Reineke et al., 2026, **P9**). The paper advances RO4 by conceptualizing workaround evaluation as a multidimensional decision problem. Drawing on an echeloned Design Science Research (eDSR) approach (Tuunanen et al., 2024) and field data from three organizations, it shows that workarounds can produce simultaneous positive and negative effects across multiple perspectives (organization, process participants, and IT artifacts) (Assbrock et al., 2024), across different time horizons (short-, mid-, and long-term), and across impact types such as quality, processing time, costs, and flexibility (Beerepoot and Van de Weerd, 2018). Moreover, workarounds are frequently interconnected through shared misfits and concatenated effects, such that evaluating them in isolation is insufficient (Löhr et al., 2025; Bartelheimer et al., 2025; Röder et al., 2014).

A central contribution is the validated problem statement explaining why ad hoc decision-making is inadequate for evaluating workarounds in practice (Assbrock et al., 2024). Building on this analysis, the paper derives and validates five design objectives that specify requirements for methods and IT artifacts supporting the evaluation of workarounds, thereby operationalizing the *Evaluate & Decide* phase of the workaround-to-innovation process (Assbrock et al., 2024). In doing so, it also extends the prevailing bug-and-fix view of misfit–workaround relations by demonstrating a web of direct and indirect effects that can evolve over time and differ across stakeholders (Alter, 2014; Soffer et al., 2023).

In line with RO4, the paper thus provides a structured foundation for the informed, data-driven evaluation of workarounds, enabling organizations to govern workarounds as a strategic input to process management and innovation rather than as unmanaged deviations (Assbrock et al., 2024; Bartelheimer et al., 2023).

## 4.2 Contribution to Research and Management

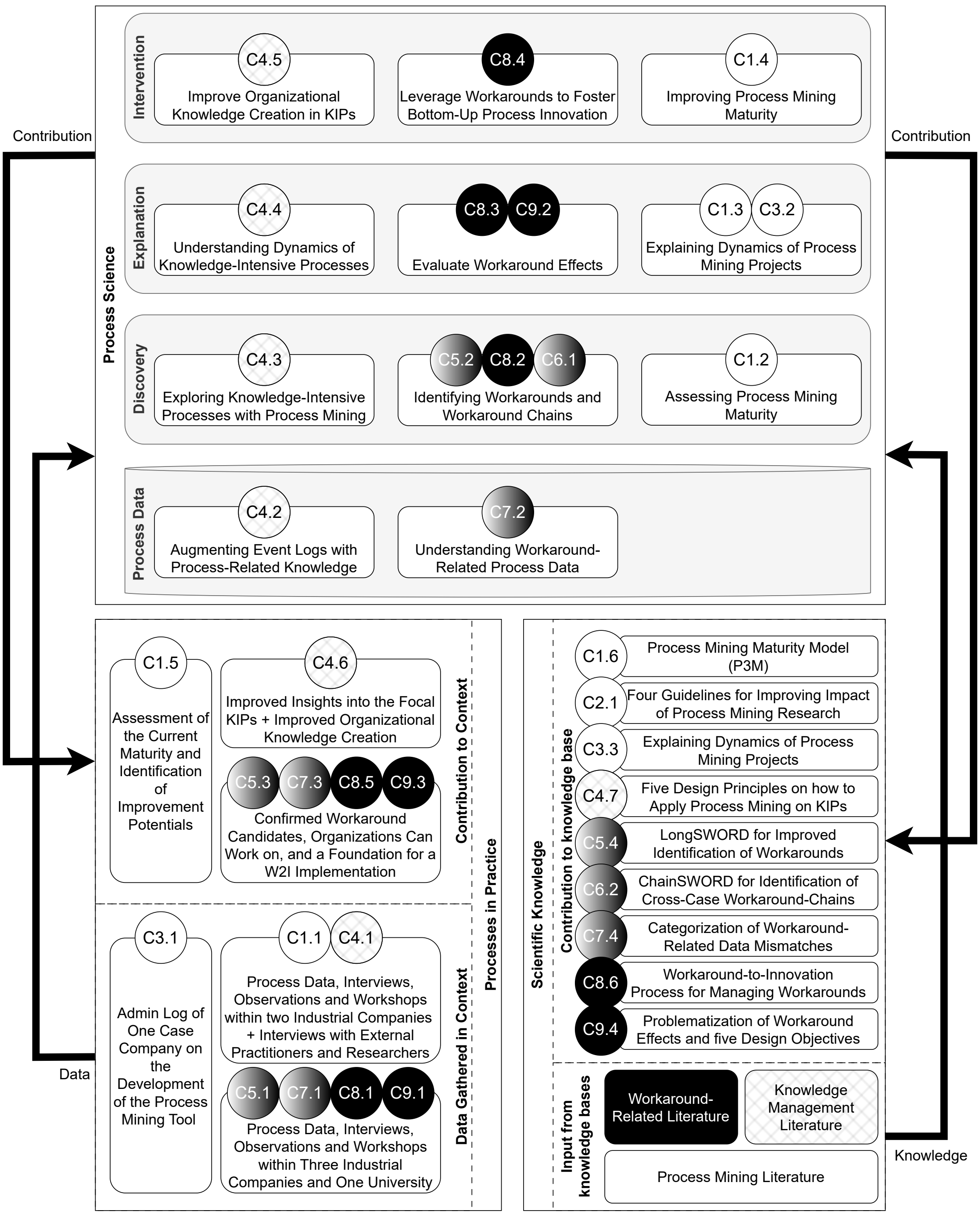


**Figure 4.7:** Contributions of this Dissertation

This dissertation is strongly rooted in both Information Systems (IS) and Business Process Management (BPM) research. The Process Science Research Framework (vom Brocke et al., 2024) provides a useful BPM-oriented lens that integrates the rigor and relevance cycles of design science research (Hevner et al., 2004) while emphasizing descriptive Omega and prescriptive Lambda knowledge (Gregor and Hevner, 2013). Within this framework, contributions relate to the activities of *discovery*, *explanation*, and *intervention*, as well as to knowledge about process data. As noted by vom Brocke et al. (2024), research endeavors may contribute to all categories or focus on specific aspects.

This distinction is reflected in the contributions of this dissertation. Some studies concentrate on individual aspects, such as the investigation of data mismatches caused by workarounds (Bartelheimer et al., 2025, **P7**), their identification (Löhr et al., 2025; Löhr, 2026, **P5 & P6**), or their explanation (Reineke et al., 2026, **P9**). Others provide broader contributions across several categories of the framework. For example, the ADR project on process mining for knowledge-intensive processes contributes to process data as well as to discovery, explanation, and intervention (Brennig et al., 2026, **P4**).

Mapping the contributions of this dissertation onto the Process Science Research framework (Figure 4.7) reveals three overarching research streams that collectively address all categories of the framework, while detailed explanations are provided in Tables 4.6 to 4.9. All streams aim to improve the understanding and management of process dynamics through process mining. This includes descriptive knowledge that supports the discovery and explanation of dynamic behavior—particularly workarounds and knowledge-intensive processes—as well as prescriptive knowledge in the form of models, methods, and artifacts that enable practitioners to intervene when such dynamics occur.

Overall, the contributions collectively provide a comprehensive set of insights and approaches that support the *discovery* and *explanation* of process dynamics, while also offering knowledge on how organizations can *intervene* when such dynamics occur.

| | **P1: "Improving Process Mining Maturity–From Intentions to Actions" (Brock et al., 2024)** | **P2: "Maximizing the Impact of Process Mining Research: Four Strategic Guidelines" (Brennig, Löhr, et al., 2024)** | **P3: "Understanding the Dynamics of a Process Mining Project - Analyzing Log Data of a Process Mining Platform" (Skolik and Löhr, 2026)** |
|---|---|---|---|
| **Knowledge base** | | Process Mining | |
| **Research Method** | Design Science Research (Becker et al. 2009) | Systematic Literature Review (Liberati et al., 2009) | Single Case Study (Yin, 2017) |
| **Data gathered in context** | (C1.1) One case company for design, development and demonstration<br>One case company for evaluation<br>Eleven interviews for gathering actions | - | (C3.1) Admin log of one case company on the development and usage activities of the process mining tool |
| **Process Data** | - | - | - |
| **Discovery** | (C1.2) The maturity model can be used to determine the current maturity of an organizations with regards to process mining maturity | - | - |
| **Explanation** | (C1.3) Combining the maturity model with the domain knowledge of process participants can provide explanations on why things as they are | - | (C3.2) Provide insights on how a process mining project worked and why it succeeded or stumbled |
| **Intervention** | (C1.4) The 30 actions gathered with practitioners and researchers help to improve the organizations maturity and processes | - | - |
| **Contribution to context** | (C1.5) Both involved companies used the maturity model to assess their current state and to identify improvement potentials | - | - |
| **Contribution to knowledge base** | (C1.6) Methodological contribution in form of the process mining maturity model & 30 actions to improve the maturity | (C2.1) Insights into the current state of process mining literature with regards to their application in practice<br>Four guidelines for improving impact of process mining research | (C3.3) Determination of four phenomena during a process mining project |

**Table 4.6:** Research Objective 1 - Contributions and Findings

To address research objective 1 (*to systematize the competencies organizations require to create value with process mining*), the systematic literature review (Brennig, Löhr, et al., 2024, **P2**) synthesized existing research and derived four guidelines that encourage researchers to focus on the practical utility and value of process mining. Within the process science research framework, **P2** primarily contributes to the knowledge base and motivated further research that investigates real-world BPM challenges (see Table 4.6).

Guided by these insights, subsequent work focused on the organizational conditions required for successful process mining adoption. The Process Mining Maturity Model (P3M) (Brock et al., 2024, **P1**) represents a key contribution in this stream. As a multi-factor maturity model, P3M enables organizations to assess and improve their process mining capabilities. The maturity assessment supports *discovery* by revealing the current organizational state, while accompanying interviews and workshops provide *explanations* for the observed conditions. To enable organizational improvement, 30 practitioner-derived actions were developed to support targeted *interventions*. Both participating organizations applied the model to assess their current maturity and identify improvement potentials. Methodologically, the maturity model and the associated actions represent contributions to the knowledge base.

Complementing this perspective, **P3** investigates the dynamics of process mining projects themselves. Based on a case study, four phenomena were identified that explain how process mining initiatives evolve over time and how they may introduce new dynamics into organizations (Skolik and Löhr, 2026, **P3**). These insights contribute to the theoretical understanding of process mining implementations.

To address research objective 2 (*to design a process mining tool that supports the mobilization of process-related knowledge in knowledge-intensive processes*), a 39-month Action Design Research (ADR) project was conducted (Brennig et al., 2026, **P4**). As typical for ADR projects, this work provides multiple contributions across the process science framework (see Table 4.7).

With regard to *process data*, the research demonstrates how event logs can be enriched with process-related knowledge. This enriched data enables improved *discovery* of patterns in knowledge-intensive processes by focusing on similar cases and leveraging contextual knowledge. Building on this, the approach supports *explanation* by enabling users to reconstruct and understand decisions made in past process instances. For *intervention*, the system facilitates the recombination of knowledge and encourages collaboration between knowledge holders.

The ensemble artifact and its insights were applied by the participating organizations. From a theoretical perspective, the study contributes a Type V design knowledge artifact (Gregor and Hevner, 2013) in the form of a process mining tool design for knowledge-intensive processes. The artifact is grounded in five theory-informed design principles (Gregor et al., 2020), which were evaluated according to the reusability criteria proposed by Iivari et al. (2021). Together, these contributions provide a theoretical framework that can be further refined and extended in future research.

After investigating intentionally dynamic settings such as knowledge-intensive processes, the dissertation turns to unintended bottom-up dynamics in organizations by addressing research objective 3 (*to systematize how workarounds can be identified and analyzed*).

| | **P4: "Design Principles for Process Mining of Knowledge-Intensive Processes: An Action Design Research Study" (Brennig et al., 2026)** |
|---|---|
| **Knowledge base** | Process Mining & knowledge-intensive processes |
| **Research Method** | Action Design Research (Sein et al., 2011) |
| **Data gathered in context** | (C4.1) Two case company for design, development, demonstration and evaluation.<br>One additional company helped with demonstration<br>Interviews with nine practitioners and 14 researchers for evaluation the design principles |
| **Process Data** | (C4.2) Process data has to be enhanced with process-related knowledge |
| **Discovery** | (C4.3) Focusing on similar instances and leveraging process-related knowledge to better depict KIPs |
| **Explanation** | (C4.4) Process-related knowledge helps to understand the individual mechanisms and decisions made by process participants. |
| **Intervention** | (C4.5) Recombining existing knowledge and the socialization between knowledge bearers helps in running processes |
| **Contribution to context** | (C4.6) Both involved companies partook and leveraged the insights from the project. |
| **Contribution to knowledge base** | (C4.7) Five evaluated theory ingrained design principles on how to create a process mining tool for KIPs. |

**Table 4.7:** Research Objective 2 - Contributions and Findings

To understand how workarounds manifest in event data, an inductive multiple case study was conducted (Bartelheimer et al., 2025, **P7**). The study identifies three categories of workaround-related mismatches between real-world processes and event data, thereby clarifying the possibilities and limitations of data-driven workaround identification approaches. This contribution primarily addresses the *process data* dimension of the process science research framework. At the same time, it advances the knowledge base by demonstrating that purely data-driven approaches are insufficient for capturing all workarounds and therefore need to be complemented with qualitative methods (van der Waal, van de Weerd, et al., 2024). The findings also provided participating organizations with insights that informed their process improvement initiatives (see Table 4.8).

Building on these insights, the LongSWORD method was developed as an extension of the SWORD framework (van der Waal, van de Weerd, et al., 2024). LongSWORD expands the original framework by introducing additional analytical steps and two cross-case patterns, thereby improving the *discovery* of workarounds while reducing the analytical effort required from process analysts (Löhr et al., 2025, **P5**). The empirical analysis also revealed the existence of workaround chains, which motivated further research in **P6** and **P9**. The participating organizations used the findings to better understand and improve their processes.

To operationalize the identification of workaround chains, **P6** integrates the SWORD framework with object-centric process mining (van der Aalst, 2019). The resulting concept, ChainSWORD, introduces five object-centric workaround patterns and adapted control-flow patterns that enable the identification of workarounds spanning multiple business objects and interconnected workaround chains (Löhr, 2026, **P6**). This conceptual contribution provides a foundation for future implementations and empirical evaluations.

| | **P5: "Forging the LongSWORD: Exaptation and Enhancement of the SWORD Framework for Workaround Detection" (Löhr et al., 2025)** | **P6: "Drafting the ChainSWORD – Towards Identifying Workaround Chains with Object-Centric Process Mining" (Löhr, 2026)** | **P7: "Workarounds as a Cause of Mismatches in Business Processes—Insights from a Multiple Case Study" (Bartelheimer et al., 2025)** |
|---|---|---|---|
| **Knowledge base** | | Process Mining & Workarounds | |
| **Research Method** | Design Science Research Methodology (Peffers et al., 2007) | Design Science Research Methodology (Peffers et al., 2007) | Multiple Case Study (Yin, 2017) |
| **Data gathered in context** | (C6.1) Event logs of two case companies | - | (C8.1) 13 Workarounds from four case organizations |
| **Process Data** | - | - | (C8.2) Systematization of workaround-related data mismatches |
| **Discovery** | (C6.2) Provide two new cross-case patterns for the SWORD framework, improved SWORD framework regarding its efficiency | (C7.1) Elevate SWORD framework to leverage an object-centric perspective. Provide five new object-centric pattern and approach to identify workaround chains | - |
| **Explanation** | - | - | - |
| **Intervention** | - | - | - |
| **Contribution to context** | (C6.3) Provide insights about the found workarounds to the companies | - | (C8.3) Provide insights about the found workarounds to the companies |
| **Contribution to knowledge base** | (C6.4) Enhanced SWORD framework with two new cross-case patterns, and means to reduce the analytical effort Provide first means to find cross-case workarounds | (C7.2) Provide ChainSWORD as theoretical concept, which can be implement in future research | (C8.4) Understanding of how workarounds manifest in data Clear outline for future data-driven workaround identification and evaluation methods |

**Table 4.8:** Research Objective 3 - Contributions and Findings

To address research objective 4 (*to design IT artifacts for managing and evaluating workarounds to foster bottom-up process innovations*), a multiple case study was conducted (Assbrock et al., 2024, **P8**). The study analyzed the evolution and management of nine workarounds and resulted in the development of the workaround-to-innovation process. This framework structures the management of workarounds across four phases that collectively support *discovery*, *explanation*, and *intervention*. In addition, six common pitfalls in workaround management were identified. The framework represents the theoretical contribution, while the participating organizations have begun implementing the process and applying the insights to their own workarounds (see Table 4.9).

Finally, **P9** addresses the complexity of evaluating the consequences of workarounds. The study formulates a problematization of workaround evaluation and derives five design objectives that future methods and systems should fulfill (Reineke et al., 2026,

| | P8: "Workarounds as Catalysts for Process Innovation: A Multiple Case Study on Pitfalls and Protocols" (Assbrock et al., 2024) | P9: "From Temporary Fixes to Informed Decisions—Design Echelons for Evaluating Workarounds" (Reineke et al., 2026) |
|---|---|---|
| **Knowledge base** | Workarounds | |
| **Research Method** | Multiple Case Study (Yin, 2017) | Echeloned Design Science Research (Tuunanen et al., 2024) |
| **Data gathered in context** | (C9.1) Nine workarounds from three case organizations | (C10.1) Nine workarounds from three case organizations |
| **Process Data** | - | - |
| **Discovery** | (C9.2) Contents of the Identify & Share and Categorize & Analyze phases of the Workaround to Innovation process | - |
| **Explanation** | (C9.3) Contents of the Evaluate & Decide phase of the Workaround to Innovation process | (C10.2) Provide means to explain the interrelation and causality between misfits, workarounds and their effects |
| **Intervention** | (C9.4) Contents of the Implement & Transform phase of the Workaround to Innovation process | - |
| **Contribution to context** | (C9.5) Provide insights about the found workarounds to the organizations<br>The organizations aim to implement the workaround-to-innovation process properly | (C10.3) Provide insights about the found workarounds to the companies |
| **Contribution to knowledge base** | (C9.6) Workaround-to-Innovation process as a structured approach for managing workarounds and as a mean to position related approaches | (C10.4) Provide a validated problematization about misfits, workarounds and their effects.<br>Further, provide five design objectives a corresponding system has to fulfill. |

**Table 4.9:** Research Objective 4 - Contributions and Findings

**P9**). This work advances the *explanation* of how workarounds interact with other organizational elements and builds upon earlier contributions in **P5**, **P6**, and **P7**.

Taken together, the overall contributions of this dissertation are threefold. First, addressing the frequent struggles organizations face when attempting to leverage process mining (Martin et al., 2021) and responding to calls for actionable guidance (Dunzer et al., 2021; Beverungen et al., 2021), the Process Mining Maturity Model (P3M) (Brock et al., 2024) enables organizations to assess and explain their process mining readiness, thereby helping to identify improvement potentials. Complementarily, insights into the dynamics of a process mining introduction project (Skolik and Löhr, 2026), combined with the improvement actions provided by P3M (Brock et al., 2024), contribute to establishing a stronger organizational foundation for leveraging process mining as a tool to manage process dynamics. Consistent with the enabling and constraining nature of technology (Beverungen, 2014), process mining is not only useful for managing dynamics but can also introduce new dynamics of its own (Skolik and Löhr, 2026; Mahringer and Walleser, 2023).

Second, the dissertation investigates intentionally dynamic BPM settings such as knowledge-intensive processes. The developed artifact and design principles for applying process mining in such contexts (Brennig et al., 2026) help address common challenges, including the fragmentation and isolation of tacit process knowledge (Ramesh and Tiwana, 1999; Di Ciccio et al., 2015). Moreover, this work provides a pathway for integrating relevant explicated knowledge, thereby enriching the contextual information available during process mining analyses—an aspect that is often missing when interpreting process mining results (Grisold, van der Aa, et al., 2024).

Third, the dissertation contributes comprehensively to the study of workarounds as unintended forms of dynamic behavior. Without intervention, workarounds tend to diffuse and become institutionalized over time (Alter, 2014). The workaround-to-innovation process (Assbrock et al., 2024) provides a framework for managing this phenomenon and for positioning contributions within the broader workaround literature.

Within this stream, the dissertation particularly advances the identification and analysis of workarounds. The systematization of workaround-induced data mismatches (Bartelheimer et al., 2025) highlights the limitations of purely data-driven identification methods (Weinzierl et al., 2021; van der Waal, van de Weerd, et al., 2024) and emphasizes the continued importance of qualitative approaches. At the same time, both approaches are complementary, as they reveal different sets of workarounds depending on the underlying misfits (Bartelheimer et al., 2023) and the willingness of process participants to disclose deviations.

Retaining the process mining lens, we extended the SWORD framework (van der Waal, van de Weerd, et al., 2024) in two ways, for one by extending the method by additional steps to allow for a more focused and efficient workaround search, reducing the overall effort from the process analyst (Löhr et al., 2025). For the other we provide means to identify workarounds spanning multiple business objects as well as interrelated workaround chains (Löhr, 2026).

Particularly, the identification of workaround chains provides a novel perspective on workarounds within IS and BPM research, as workarounds have often been considered to be in a 1:1 relation to their misfits. This more wholistic view is in line with recent trends in process mining like OCPM (Berti and van der Aalst, 2023), emphasizing how processes are boundary spanning in terms of business objects, resources like systems and personnel, and organization-each enabling and limiting each other (Beverungen, 2014).

Finally, to support more informed decision-making regarding workarounds (Beerepoot and Van de Weerd, 2018), the dissertation problematizes the complex consequences of workarounds and translates them into design goals for future evaluation approaches (Reineke et al., 2026). These goals have already inspired subsequent work, such as the Workaround Modeling Notation (Krabbe et al., 2025).

## 4.3 Conclusion and Outlook

The aims of this dissertation were twofold: first, to derive descriptive knowledge on dynamic behavior within business processes, particularly regarding knowledge-intensive processes and workarounds; and second, to develop prescriptive knowledge on how to intervene in and steer these dynamics. Choosing process mining as the primary approach to realize this endeavor provided a data-driven lens on inherently socio-technical processes.

Therefore, one crucial part of this dissertation was to demonstrate how process mining can be applied to knowledge-intensive processes, with the essential addition of gathering and analyzing additional process-related knowledge. During the course of the presented studies, artificial intelligence—particularly large language models—gained traction among researchers, practitioners, and consumers alike (Vidgof et al., 2023; Rosemann et al., 2024). As large language models excel at understanding and structuring natural language, they constitute an extremely promising tool for improving the explication of tacit knowledge as well as its recombination, which should be explored further in future research.

In addition, our research on workarounds lays an important foundation, but further work is required to effectively enact comprehensive workaround management in organizations. To this end, the workaround-to-innovation process—developed to answer RO4—still needs to be properly institutionalized within case organizations. In particular, evaluation and assessment remain challenging tasks, especially in light of newly identified phenomena such as workaround chains.

Workaround chains are just one of many examples demonstrating the need for a more holistic view of organizational phenomena. IS and BPM research focus on how organizations operate and leverage IT to create value; however, they have often tended to examine phenomena such as workarounds and deviance in isolation. The same is true for traditional process mining, which frequently focuses narrowly on individual processes while neglecting endogenous and exogenous influences. Recent paradigm shifts such as object-centric process mining (van der Aalst, 2023), which promote a holistic view of processes and their interconnectedness, offer promising avenues for gaining a deeper understanding of the complex interactions within organizations (Beverungen et al., 2021). Nonetheless, technical challenges—such as the complexity of the underlying data structures and their partial incompatibility with existing approaches—as well as organizational challenges—such as establishing a shared process understanding and collecting high-quality process data, particularly interaction data—remain important topics for future research.

The investigation of workarounds and knowledge-intensive processes in this dissertation has revealed both differences and commonalities with respect to their dynamics. The key difference relates to intentionality: knowledge-intensive processes are intentionally dynamic, whereas workarounds introduce dynamics into processes unintentionally, as they often arise out of necessity to keep individual process instances running—something that many still deem primarily harmful. This predominantly negative view of workarounds should evolve toward recognizing their potential as a source of bottom-up process innovation (Bartelheimer et al., 2023).

At the same time, both phenomena share a crucial commonality: the central role of people. While endogenous (Andrews, Suriadi, Wynn, et al., 2018) and exogenous events (Röglinger et al., 2022) affect every process, process participants respond to these events by enacting the necessary deviations. They represent the original creative source of innovation and improvement. Therefore, involving process participants and other stakeholders is key to transforming dynamic behavior into organizational benefits—whether by adopting and adapting creative solutions, addressing underlying issues, or combining both approaches. Successfully managing such process dynamics can therefore contribute to sustained competitive advantage in increasingly volatile environments (vom Brocke et al., 2024).

# Part B
# Included Publications

# 1 RO1: Process Mining Competencies

## 1.1 Improving Process Mining Maturity: From Intentions to Actions

| | | |
|---|---|---|
| **Title** | **Improving Process Mining Maturity: From Intentions to Actions** | |
| **Publication Type** | Journal | |
| **Publication Outlet** | Business & Information Systems Engineering | |
| **VHB JOURQUAL3:** | B | |
| **VHB JOURQUAL4:** | B | |
| **Authors** | **Name** | **Contribution** |
| | Jonathan Brock | 30% |
| | Katharina Brennig | 30% |
| | Bernd Löhr | 20% |
| | Christian Bartelheimer | 16% |
| | Sebastian von Enzberg | 2% |
| | Roman Dumitrescu | 2% |
| **Status** | Published | |
| **Presentation** | – | – |
| **Full Citation** | J. Brock, K. Brennig, B. Löhr, C. Bartelheimer, S. von Enzberg, and R. Dumitrescu 2024. “Improving Process Mining Maturity–From Intentions to Actions,” *Business & Information Systems Engineering* (66:5), pp. 585–605. (doi: 10.1007/s12599-024-00882-7) | |

**Table 1.1: Fact sheet of Publication P1**

**Abstract.** Process mining is advancing as a powerful tool for revealing valuable insights about process dynamics. Nevertheless, the imperative to employ process mining to enhance process transparency is a prevailing concern for organizations. Despite the widespread desire to integrate process mining as a pivotal catalyst for fostering a more agile and flexible Business Process Management (BPM) environment, many organizations face challenges in achieving widespread implementation and adoption due to deficiencies in various dimensions of process mining readiness. The current Information Systems (IS) knowledge base lacks a comprehensive framework to aid organizations in augmenting their process mining readiness and bridging this intention-action gap. This paper presents a Process Mining Maturity Model (P3M), refined through multiple iterations, encompassing five factors and 23 elements that organizations must address to increase their process mining readiness. The maturity model advances the understanding of how to close the intention-action gap of process mining initiatives in multiple dimensions. Furthermore, insights from a comprehensive analysis of data gathered in eleven qualitative interviews are drawn, elucidating 30 possible actions that organizations can implement to establish a more responsive and dynamic BPM environment by the means of process mining.

## 1.2 Maximizing the Impact of Process Mining Research: Four Strategic Guidelines

| | | |
|---|---|---|
| **Title** | **Maximizing the Impact of Process Mining Research: Four Strategic Guidelines** | |
| **Publication Type** | Conference | |
| **Publication Outlet** | Americas Conference on Information Systems (AMCIS) | |
| **VHB JOURQUAL3:** | D | |
| **VHB JOURQUAL4:** | C | |
| **Authors** | **Name** | **Contribution** |
| | Katharina Brennig | 35% |
| | Bernd Löhr | 25% |
| | Jonathan Brock | 25% |
| | Malte Reineke | 5% |
| | Christian Bartelheimer | 10% |
| **Status** | Published | |
| **Presentation** | Malte Reineke | 100% |
| **Full Citation** | K. Brennig, B. Löhr, J. Brock, M. Reineke, and C. Bartelheimer 2024. "Maximizing the Impact of Process Mining Research: Four Strategic Guidelines," in *Americas Conference on Information Systems (AMCIS)*,. URL: https://aisel.aisnet.org/amcis2024/dsa/dsa/14 | |

**Table 1.2: Fact sheet of Publication P2**

**Abstract.** While most organizations recognize the potential of process mining and plan to start process mining initiatives, significant challenges for applying process mining in organizations remain unsolved. In this paper, we investigate the utility of process mining in organizations. Although process mining papers in the current Information Systems (IS) knowledge base deal with developed artifacts based on real-world scenarios, they often do not adequately reflect on their results' utility and effectiveness in the application context, diminishing their contributions' practical and theoretical implications. By discussing the results from the systematic literature review in the backdrop to the existing knowledge base, we develop four strategic guidelines for conducting process mining research with high relevance and managerial impact. Fellow researchers can follow these guidelines to rigorously plan, execute, and evaluate process mining research projects to generate business value and achieve maximum organizational impact.

## 1.3 Understanding the Dynamics of a Process Mining Project - Analyzing Log Data of a Process Mining Platform

| | | |
|---|---|---|
| **Title** | **Understanding the Dynamics of a Process Mining Project - Analyzing Log Data of a Process Mining Platform** | |
| **Publication Type** | Conference | |
| **Publication Outlet** | International Conference on Business Process Management - Workshops (BPM) | |
| **VHB JOURQUAL3:** | D | |
| **VHB JOURQUAL4:** | C | |
| **Authors** | **Name** | **Contribution** |
| | Alexander Skolik | 75% |
| | Bernd Löhr | 25% |
| **Status** | Published | |
| **Presentation** | Alexander Skolik | 100% |
| **Full Citation** | A. Skolik and B. Löhr 2026. "Understanding the Dynamics of a Process Mining Project - Analyzing Log Data of a Process Mining Platform," in *Business Process Management Workshops*, I. van de Weerd, B. Estrada Torres, and H. van der Aa (eds.). Cham: Springer Nature Switzerland | |

**Table 1.3: Fact sheet of Publication P3**

**Abstract.** Process mining proved to be valuable for enabling transparency in business processes and to help to manage the everyday process dynamics. But what about the dynamics of a process mining project itself. In this paper, we present insights of a process mining introduction project spanning two years. For that we analyze the logs of the process mining platform supported by interviews of the developers and participants as part of our case study research. Based on this, our findings indicate four actions that impact a successful process mining project and the underlying dynamics. (1) two development phases in a test and productive environment can lead to data driven process improvements. (2) maintenance and the associated technical debt can cause process drift. (3) scope creep of the project is easily identifiable in such logs and hinders the complete process mining initiative and (4) a sufficient user base and constant interaction with allows for bottom up process change. These results provide quantitative insights into the development and adoption cycles of the software and the direct impact on the processes as well as the business process management initiative. From this initial analysis researchers can benefit from first insights into the qualitative side of a process mining project and our categorization of the findings. Practitioners can use the findings as a blueprint or source for improvements to their process mining projects.

# 2 RO2: Process Mining of Knowledge-Intensive Processes

## 2.1 Design Principles for Process Mining of Knowledge-Intensive Processes: An Action Design Research Study

| | | |
|---|---|---|
| **Title** | **Design Principles for Process Mining of Knowledge-Intensive Processes: An Action Design Research Study** | |
| **Publication Type** | Journal | |
| **Publication Outlet** | The Journal of Strategic Information Systems (JSIS) Currently published via *Working Paper Series, Paderborn University* | |
| **VHB JOURQUAL3:** | A | |
| **VHB JOURQUAL4:** | A | |
| **Authors** | **Name** | **Contribution** |
| | Katharina Brennig | 40% |
| | Christian Bartelheimer | 25% |
| | Bernd Löhr | 20% |
| | Daniel Beverungen | 10% |
| | Oliver Müller | 5% |
| **Status** | under review (2nd revision phase) | |
| **Presentation** | – | – |
| **Full Citation** | K. Brennig, C. Bartelheimer, B. Löhr, D. Beverungen, and O. Müller 2026. “Design Principles for Process Mining of Knowledge-Intensive Processes: An Action Design Research Study,” *Working Papers Dissertations 166, Paderborn University, Faculty of Business Administration and Economics* (). under review (2nd revision phase) | |

**Table 2.1: Fact sheet of Publication P4**

**Abstract.** Knowledge-intensive processes (KIPs) are strategic core processes that drive organizational value creation and competitive advantage. Despite their strategic importance, KIPs are predominantly managed manually, as existing classes of IT systems either lack process awareness or struggle with the complexity and unpredictability of KIPs. We present findings from a 39-month Action Design Research (ADR) project to conceptualize a new class of IT artifacts that enables process mining of KIPs. This class of IT artifacts integrates richer process-related information, facilitating knowledge transfer by allowing process participants to learn from similar process instances and engage in socialization at run-time. Our research bridges critical gaps between business process management (BPM) and knowledge management, offering theoretical and managerial insights. We propose five theory-ingrained design principles that guide the development of process mining systems for KIPs and examine their role in fostering knowledge creation within organizations, ultimately upgrading strategic decision-making and organizational performance.

# 3 RO3: Process Mining of Workarounds

## 3.1 Forging the LongSWORD: Exaptation and Enhancement of the SWORD Framework for Workaround Detection

| | | |
|---|---|---|
| **Title** | **Forging the LongSWORD: Exaptation and Enhancement of the SWORD Framework for Workaround Detection** | |
| **Publication Type** | Conference | |
| **Publication Outlet** | International Conference on Business Process Management - Workshops (BPM) | |
| **VHB JOURQUAL3:** | D | |
| **VHB JOURQUAL4:** | C | |
| **Authors** | **Name** | **Contribution** |
| | Bernd Löhr | 25% |
| | Christian Bartelheimer | 15% |
| | Frank Köhne | 15% |
| | Sina Nordlohne | 15% |
| | Daniel Alile | 15% |
| | Andrees Latten | 15% |
| **Status** | Published | |
| **Presentation** | Bernd Löhr | 100% |
| **Full Citation** | B. Löhr, C. Bartelheimer, F. Köhne, S. Nordlohne, D. Alile, and A. Latten 2025. "Forging the LongSWORD: Exaptation and Enhancement of the SWORD Framework for Workaround Detection," in *Business Process Management Workshops*, K. Gdowska, M. T. Gómez-López, and J.-R. Rehse (eds.). Cham: Springer Nature Switzerland, pp. 319–331. (doi: 10.1007/978-3-031-78666-2_24) | |

**Table 3.1: Fact sheet of Publication P5**

**Abstract.** Workarounds are goal-driven adaptations of business processes that employees implement to overcome perceived constraints at work. While process deviations can be easily detected with data-driven methods like process mining, it is hard to distinguish workarounds from related, yet distinct, concepts. The SWORD framework constitutes a state-of-the-art method for the data-driven detection of workarounds in business process event logs based on pre-defined patterns extracted from support processes in the healthcare domain. However, currently, SWORD has solely been applied to highly standardized processes with low variation and knowledge intensity, while it can be assumed that workarounds more often appear in the latter and also bear bigger potential for innovating processes. Furthermore, SWORD neither comprises data preparation steps nor enables the analysis of workarounds and their implications for the organization. In this paper, we develop an exaptation of the existing SWORD framework, coined LongSWORD, together with two industrial case organizations. Our contribution to theory and practice is threefold. First, we present a framework that enables the preparation of a meaningful event log in alignment with according process model or routine. Second, the detection and analysis of workarounds in core industrial processes is enabled by adding two new cross-case patterns. Third, the LongSWORD method enables others to assess the implications of workarounds beyond its individual implementers.

## 3.2 Drafting the ChainSWORD – Towards Identifying Workaround Chains with Object-Centric Process Mining

| | | |
|---|---|---|
| **Title** | **Drafting the ChainSWORD – Towards Identifying Workaround Chains with Object-Centric Process Mining** | |
| **Publication Type** | Conference | |
| **Publication Outlet** | European Conference on Information Systems (ECIS) | |
| **VHB JOURQUAL3:** | B | |
| **VHB JOURQUAL4:** | A | |
| **Authors** | **Name** | **Contribution** |
| | Bernd Löhr | 100% |
| **Status** | Published | |
| **Presentation** | Bernd Löhr | 100% |
| **Full Citation** | B. Löhr 2026. "Drafting the ChainSWORD – Towards Identifying Workaround Chains with Object-Centric Process Mining," in *European Conference on Information Systems*, URL: https://aisel.aisnet.org/ecis2026/bpm/bpm/5 | |

**Table 3.2: Fact sheet of Publication P6**

**Abstract.** Workarounds recently gained traction in research in practice, as they signal underlying issues in processes, but also reveal potential for bottom-up innovation. Process managers can leverage these purposeful deviations from standard operating procedures, to identify and resolve the responsible organizational or technical misfit. However, those might be caused by other prior workarounds, resulting in workaround chains. Existing research predominantly classifies individual workarounds and their corresponding misfit, neglecting the broader organizational interactions. This Research-in-Progress paper presents an object-centric process mining approach to quantitatively identify potential workaround chains. Our approach builds on the state-of-the-art framework called Semi-automated WORkaround Detection (SWORD), which is now extended to leverage an object-centric perspective. Our new artifact, the ChainSWORD comprises five new object-centric patterns, leverages an advanced case notion and enables the identification of potential workaround chains. However, it remains to be fully implemented and validated as a software solution as part of future research.

## 3.3 Workarounds as a Cause of Mismatches in Business Processes—Insights from a Multiple Case Study

| | | |
|---|---|---|
| **Title** | **Workarounds as a Cause of Mismatches in Business Processes—Insights from a Multiple Case Study** | |
| **Publication Type** | Journal | |
| **Publication Outlet** | Business & Information Systems Engineering | |
| **VHB JOURQUAL3:** | B | |
| **VHB JOURQUAL4:** | B | |
| **Authors** | **Name** | **Contribution** |
| | Christian Bartelheimer | 30% |
| | Bernd Löhr | 30% |
| | Malte Reineke | 20% |
| | Agnes Aßbrock | 15% |
| | Daniel Beverungen | 5% |
| **Status** | Published | |
| **Presentation** | Bernd Löhr (presented at the BPM Conference 2025 as part of the Journals First track) | 100% |
| **Full Citation** | C. Bartelheimer, B. Löhr, M. Reineke, A. Aßbrock, and D. Beverungen 2025. “Workarounds as a Cause of Mismatches in Business Processes—Insights from a Multiple Case Study,” *Business & Information Systems Engineering* (67:3), pp. 339–356. (doi: 10.1007/s12599-025-00943-5) | |

**Table 3.3: Fact sheet of Publication P7**

**Abstract.** Process mining has been established as a data-driven approach to analyze and improve business processes based on event data documented in event logs. A core assumption for meaningful analyses is that event data accurately represent the real-world execution of business processes in an organization. However, anecdotal evidence and recent case studies show that these aspects do not always align, and the business process management community is only beginning to investigate the mechanisms generating mismatches between process execution and event data. This study aims to identify the role of workarounds—goal-directed deviations from standard processes performed by process participants to overcome obstacles—in this context. Through an inductive multiple case study of 13 workarounds in four organizations, three mismatch categories between event logs and real-world process execution related to workarounds are identified and explored. This study contributes to the literature by describing how workarounds can act as mechanisms that cause mismatches between process execution and event data, adding to the discussion on process drift and workaround mining. Furthermore, exploring the mismatch categories offers insights for practitioners and researchers on how to handle and interpret data quality issues in event data.

# 4 RO4: Management and Evaluation of Workarounds

## 4.1 Workarounds as Catalysts for Process Innovation: A Multiple Case Study on Pitfalls and Protocols

| | | |
|---|---|---|
| **Title** | **Workarounds as Catalysts for Process Innovation: A Multiple Case Study on Pitfalls and Protocols** | |
| **Publication Type** | Conference | |
| **Publication Outlet** | International Conference on Information Systems (ICIS) | |
| **VHB JOURQUAL3:** | A | |
| **VHB JOURQUAL4:** | A | |
| **Authors** | **Name** | **Contribution** |
| | Agnes Aßbrock | 35% |
| | Bernd Löhr | 30% |
| | Christian Bartelheimer | 20% |
| | Daniel Beverungen | 15% |
| **Status** | Published | |
| **Presentation** | Christian Bartelheimer | 100% |
| **Full Citation** | A. Assbrock, B. Löhr, C. Bartelheimer, and D. Beverungen 2024. "Workarounds as Catalysts for Process Innovation: A Multiple Case Study on Pitfalls and Protocols," in *International Conference on Information Systems (ICIS) Proceedings*, Bangkok, Thailand. URL: https://aisel.aisnet.org/icis2024/org_busproc/org_busproc/5/ | |

**Table 4.1: Fact sheet of Publication P8**

**Abstract.** Workarounds are intentional deviations from standard business processes performed by process participants to resolve misfits that constrain their effectiveness or efficiency. Although potential catalysts for process innovation, workarounds are frequently undervalued as temporary fixes of misfits faced on an individual level. This study analyzes nine workarounds across three organizations through a multiple case study, examining how organizations either succeed or fail in leveraging workarounds for process innovation. Our findings indicate that successful process innovation with workarounds requires robust governance, effective communication among stakeholders, and transparent decision-making processes. These protocols are particularly critical when discrepancies exist between the misfits perceived by individual participants and those at the organizational level. Our research connects individual workaround efforts to broader organizational process innovation and offers actionable guidelines for managers. These insights help position workarounds as catalysts from dynamic process innovation, thereby complementing traditional top-down process re-design approaches.

## 4.2 From Temporary Fixes to Informed Decisions—Design Echelons for Evaluating Workarounds

| | | |
|---|---|---|
| **Title** | **From Temporary Fixes to Informed Decisions—Design Echelons for Evaluating Workarounds** | |
| **Publication Type** | Conference | |
| **Publication Outlet** | International Conference on Business Process Management - Main Conference (BPM Conference) | |
| **VHB JOURQUAL3:** | C | |
| **VHB JOURQUAL4:** | B | |
| **Authors** | **Name** | **Contribution** |
| | Malte Reineke | 35% |
| | Bernd Löhr | 30% |
| | Agnes Aßbrock | 20% |
| | Christian Bartelheimer | 10% |
| | Daniel Beverungen | 5% |
| **Status** | Published | |
| **Presentation** | Malte Reineke | 100% |
| **Full Citation** | M. Reineke, B. Löhr, A. Aßbrock, C. Bartelheimer, and D. Beverungen 2026. "From Temporary Fixes to Informed Decisions—Design Echelons for Evaluating Workarounds," in *Business Process Management*, A. Senderovich, C. Cabanillas, I. Vanderfeesten, and H. A. Reijers (eds.). Vol. 16044. Lecture Notes in Computer Science. Cham: Springer Nature Switzerland, pp. 541–557. (doi: 10.1007/978-3-032-02867-9_32) | |

**Table 4.2: Fact sheet of Publication P9**

**Abstract.** Workarounds are purposeful deviations from standard operating procedures within organizations, implemented by employees to bypass misfits. The extant research predominantly focuses on classifying workaround types, identifying their causes, and unveiling why they are performed by individual initiators. However, workarounds are often viewed merely as temporary fixes, while there is no method to evaluate their positive and negative consequences in a way that can inform organizational decision-making. In this paper, we address this gap by conducting the initial phases of an echelon design science research project—problem analysis and objectives definition—to design a method enabling informed decisions about workarounds. Using a medium-sized manufacturing company as a case organization, our validated problem statement reveals that evaluating workarounds necessitates a comprehensive consideration of specific organizational, technological, and participant-centric factors. Our findings result in five design objectives that guide the development of IT artifacts for evaluating the implications of workarounds in organizations.

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