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

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Highlights

Design Principles for Process Mining of Knowledge-Intensive Processes: An Action Design Research Study[1]

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- We report an ADR study developing a new class of IT artifacts that enables process mining of knowledge-intensive processes.
- We provide five theory-ingrained design principles for process mining that build on rich information, facilitate learning from similar process instances, and stimulate socialization among process participants.
- We examine the role of the process mining artifact in fostering process-related knowledge creation.
- We offer organizations insights on how to manage knowledge-intensive processes and make strategic decisions.

[1] A prior version of this work has been published under https://ideas.repec.org/p/pdn/dispap/148.html

Design Principles for Process Mining of Knowledge-Intensive Processes: An Action Design Research Study[2]

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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.

1. Introduction

Knowledge-intensive processes (KIPs) [1], such as research and development or product innovation [2], represent a strategic dimension of modern organizations [3], as they enable firms to leverage specialized knowledge for competitive advantage [4, 5, 6, 7, 8, 9]. KIPs are strongly shaped by individuals' tacit knowledge, creativity, and decision-making competence, which makes them less structured and more complex than operational business processes [1, 10, 2, 11]. Whereas operational processes are often supported by advanced technologies such as process mining or AI agents, KIPs remain highly dependent on individual expertise [12]. This limited technological support stems from the fact that KIPs exhibit high complexity and low predictability, which current technologies address only partially [1]. Moreover, knowledge about KIPs—comprising tacit and explicit knowledge about activities, steps, and procedures [13]—is often fragmented or inconsistent, producing unreliable support and reducing the applicability of existing technologies.

Because process-related knowledge is rarely managed systematically and cross-boundary communication is often weak, much of the expertise needed to conduct KIPs remains confined to departmental silos, communities of practice, or day-to-day practices of process participants [13]. As a result, KIPs depend heavily on tacit knowledge [1, 10, 11] that is not easily accessible by others or technology. This knowledge fragmentation leads to repeated mistakes and prevents process participants from leveraging insights from previous cases [13]. The problem becomes particularly acute when employees leave the organization—whether through turnover or retirement—without effective knowledge transfer. While such issues may be less pronounced in highly standardized operational processes, they are especially challenging in KIPs. In such processes, the ability to transfer knowledge efficiently, resolve problems quickly, and innovate continuously is vital for organizational success [14, 15]. Firms must, therefore, establish mechanisms to analyze, observe, and systematically manage KIPs, while developing a robust knowledge base for future use.

Process mining has emerged as a promising approach for analyzing and managing business processes in a data-driven manner [16, 17], particularly focusing on operational processes that exhibit high levels of standardization and digitalization, such as order fulfillment or shipping [16, 18, 17]. However, three challenges impede the direct application of process mining to KIPs. First, process mining builds on event logs that capture explicit process-related knowledge such as activities, control flows, and resources [18, 17]. KIPs, in contrast, rely heavily on tacit knowledge—experience, skills, and judgments embedded in process participants' practices—that is essential for execution but absent from event logs [19, 1, 13]. Tacit knowledge is typically shared through socialization and interaction [20], yet current

[2]A prior version of this work has been published under `https://ideas.repec.org/p/pdn/dispap/148.html`

process mining approaches lack mechanisms to support these modes of knowledge conversion. Second, process mining assumes a predefined process model be embedded in a business process management system (BPMS), enabling discovery, conformance checking, and enhancement across process instances [18, 17]. KIPs, however, often lack such models and are supported by tools other than BPMS, shifting the focus toward context-specific enactments where deviations may add value rather than signal non-compliant behavior or inefficiency [1, 2, 10, 11]. Third, process mining typically analyzes completed process instances for purposes of re-design [18, 17], whereas long-running KIPs demand mobilization of knowledge during run-time to maximize their strategic value [1, 10, 2, 11, 3]. This focus on process instances requires process mining to move beyond retrospective analysis toward offering actionable guidance for process participants.

To address this gap, we develop a type five theory for design and action [21], articulated as theory-ingrained design principles [22, 23] for a new class of IT artifacts coined "*process mining of KIPs*". We draw on the theory of organizational knowledge creation, particularly the SECI model [20], as a kernel theory to inform our design process. Building on the SECI model's abstract modes of knowledge conversion—socialization, externalization, combination, and internalization—we specify mechanisms that enable process mining to support the management of KIPs. Our theory for design and action targets the mobilization of tacit knowledge, allows process participants to learn from related process instances whilst performing a process, and promotes socialization among knowledge bearers. Taken together, these mechanisms move beyond the current limitations of process mining, enabling new ways to create and use process-related knowledge in organizations.

We conducted a 39-month Action Design Research (ADR) study [24] including two case organizations and one technology provider, encompassing three iterations of building, intervention, and evaluation. Through these iterations, we designed and evaluated a contextualized IT artifact for process mining of KIPs, applying it to two representative cases—a product innovation process and an engineer-to-order process. The ADR approach ensured both the artifact's practical utility and the abstraction of design principles as generalizable knowledge. In line with the dual mission of Design Science Research (DSR), our study addresses a meaningful business problem while contributing new design knowledge to the academic literature.

Our results have implications for both theory and practice. From a business process management (BPM) perspective, the design principles specify how process mining ought to be designed to support the management of KIPs as strategic processes in organizations. From a knowledge management perspective, the design principles operationalize the abstract knowledge conversion mechanisms of the SECI model with concrete mechanisms for generating process-related knowledge through process mining. From a managerial perspective, organizations can apply our design principles to build process mining tools for KIPs and improve the management of their strategic processes.

The remainder of this paper is structured as follows. In section two, we synthesize related research on process mining and knowledge management with a focus on KIPs. Section three outlines our ADR process, and section four describes the three conducted iterations. In section five, we present five design principles and discuss the implications of our findings in section six, before concluding our paper in section seven.

2. Execution and Management of Knowledge-Intensive Processes

2.1. Process Mining of Knowledge-Intensive Processes

Process mining is a state-of-the-art approach for analyzing business processes based on data [16, 17]. At its core, it extracts event logs from information systems, which contain metadata about process execution (e.g., which activity was performed, when, for how long, and by whom) [17, 16]. From event logs, as-is processes can be discovered and further analyzed using data mining and machine learning algorithms to evaluate and improve performance [16, 17]. Process mining enables organizations to eliminate bottlenecks, support automation, and reduce process costs [17]. Its capability to process and analyze data in real time [17, 25] provides live insights into ongoing executions and allows ad hoc, data-driven decisions [26], if sufficiently detailed process data are available and can be analyzed. In doing so, organizations can strengthen their dynamic capabilities to adapt to exogenous influences [27], while enhancing the distinctiveness of their processes as a source of sustained competitive advantage [28].

Current process mining approaches are most effective for highly digitalized and standardized processes, as they rely on large volumes of accurate data [16, 17]. However, organizations also conduct many processes that are less digitized and less structured [1, 10, 2, 11]. A prominent category is KIPs [1], 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*" [1, p. 5]. In industrial contexts, KIPs include, for example, product development, where approved concepts are iteratively transformed into market-ready products, and product innovation processes, in which organizations generate and evaluate novel ideas. Such processes are of strategic importance for organizations, because they directly shape innovation and competitive advantage [2, 3, 29, 13].

KIPs are difficult to predict [10, 19], digitize, and standardize [10], due to their inherent complexity, the flexibility they require [2, 10, 30], and the ambiguity of their inputs and outputs [1]. Human-centered and knowledge-intensive activities play a pivotal role in KIPs [1, 19], enabling innovation [29] but also increasing variability, as task sequences depend on individual decisions and unforeseen events [1]. As a result, each process instance reflects the situated actions and judgments of one or more participants [1, 10, 2, 11, 31]. The strong involvement of humans is the main source of KIPs' complexity [3], complicating their mapping to predefined process models [1] and giving rise to numerous process variants [1, 2, 10, 11]. Moreover, KIPs often involve unplanned and unscheduled knowledge development [1], making each instance heavily dependent on the in-situ actions and decisions made by participants [1, 10, 2, 11, 3].

Surprisingly few attempts have been made to extend process mining to KIPs. Related research has proposed data mining techniques, such as extracting the flow of speech acts from event logs to support process performance analysis [32], or using clustering and classification to detect hidden patterns in KIPs and generate improvement recommendations [29]. Focusing on design support, mining and recommending templates for new KIPs through agenda-driven case management [33] and new recommendation systems drawing on previously handled cases [34] have been suggested. In manufacturing, process mining has been applied to product innovation processes, for example, by identifying and analyzing maintenance operations in cellular manufacturing [35]. Also, process mining has been combined with case-based reasoning [36] or with features of natural language processing to predict lead times of product innovation processes [37]. Beyond industry, process mining has also been applied in healthcare to examine treatment, diagnostic, and organizational tasks [38]. While these studies advance the knowledge base, they all rely primarily on classic process-related knowledge documented in event logs, neglecting a richer perspective on the experience, skills, and situated decision-making of process participants—all central drivers of KIPs.

2.2. Challenges of Knowledge Creation with Traditional Process Mining

The ability to create knowledge, rapidly disseminate it, and integrate it into new products and services characterizes a successful organization [13]. To create process-related knowledge, an organization must access and integrate process participants' knowledge about a process into the organization's knowledge system [39, 5], because organizations cannot create knowledge independently [5]. However, while existing organizational knowledge systems—used to support the management of tacit and explicit knowledge [4] (e.g., document management systems, collaboration and communication platforms, etc.)—allow flexible communication and collaboration among individuals to generate and share knowledge [7, 8], they mainly focus on individual tasks and lack an end-to-end process perspective [40, p.162].

Still, the theory of organizational knowledge creation—and in particular the SECI model [20]—provides a strong conceptual foundation for knowledge transformation. At its core, the model emphasizes that mobilizing and converting tacit to explicit knowledge—and vice versa—is the cornerstone of knowledge generation [20]. To expand knowledge beyond individuals (ontological dimension), tacit knowledge must be made explicit (epistemological dimension) [5, 20]. Unlike other approaches in knowledge management, which capture only partial dynamics (e.g., [41] or [42]), the SECI model systematically conceptualizes this bidirectional conversion and accounts for multi-level amplification of knowledge [20], which are both highly relevant for KIPs.

The SECI model describes four modes of knowledge conversion. In socialization, individuals acquire tacit knowledge by learning from the experiences of others, for example, in product development through collaborative workshops or informal discussions. Externalization refers to articulating tacit knowledge to make it explicit and shareable, such as when expert insights are documented during prototyping or when quality improvement meetings generate new concepts. Combination describes the synthesis of explicit knowledge into structured knowledge systems, for instance, by integrating market research, patent databases, customer feedback, and prior project reports to create a new product concept or road map. Finally, internalization occurs when individuals absorb explicit knowledge through experience, such as learning by doing. In product innovation, engineers internalize design guidelines and test results during prototyping and several iterations, gradually developing intuitive judgment that informs creative problem-solving and design decisions [20, 43, 5, 13]. Together, these modes drive organizational knowledge creation and enhance individual knowledge in an organization-wide effort that transcends departments, divisions, and organizational boundaries, beginning with individuals and progressing to larger communities of interaction [20, 43].

The SECI model provides a logical theoretical foundation for reviewing how process mining can leverage the creation of process-related knowledge (see Figure 1). In general, process-related knowledge comprises tacit and explicit knowledge about activities, steps, and procedures in a process [13]. Due to its reliance on event logs, process mining focuses on analyzing explicit process-related knowledge [44, 20] on a processes' activities, control flow, time, and other resources [18, 17]. Explicit process-related knowledge can, in this sense, be equated to information—knowledge that is articulated and presented in the form of text, graphics, words, or other symbolic forms [7]. In this sense, event logs contain data traces that provide an incomplete, yet a convenient to analyze and potentially informative representation of a process.

Tacit process-related knowledge, on the other hand, is more difficult to formalize and communicate because it is personal and context-specific [20, 44]. Tacit process-related knowledge resides in the skills and experiences of process participants and is reflected in their day-to-day practices and decision-making [13, 20, 1]. For this reason, each process participant possesses tacit process-related knowledge tied to the execution of their specific tasks within a process instance, underscoring its central importance in KIPs [13, 1]. Product development exemplifies this distinction: While explicit process-related knowledge, such as design specifications or test protocols, can be codified and documented, effective outcomes also depend on engineers' tacit process-related knowledge, such as their expertise, creativity, and experiential judgment. However, tacit process-related knowledge is rarely shared within the organization and not normally included in event logs, limiting its dissemination [1]. Still, even though some process-related knowledge is initially tacit, a part of it can be externalized and integrated into the processes and products of an organization [15]. Current process mining, however, provides no mechanisms for incorporating this type of knowledge, constraining its analytical quality [45] since only a subset of all available process-related knowledge relevant to KIPs can be analyzed [11, 10].

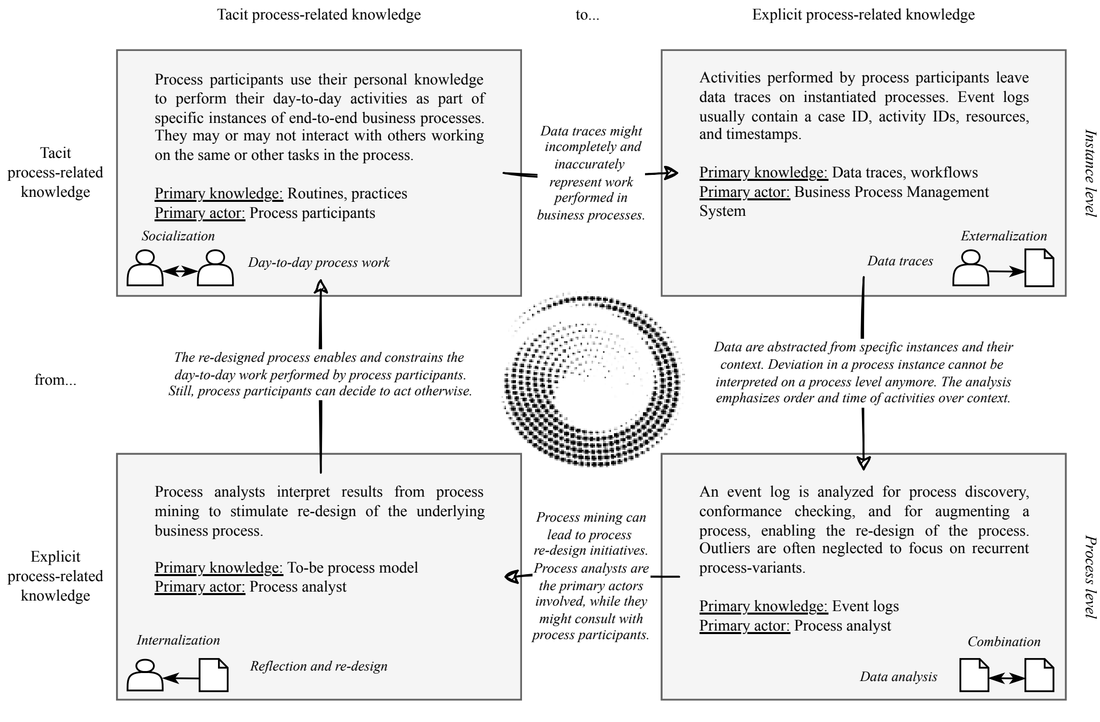


Figure 1: Process mining of organizational knowledge creation in operational processes

Another challenge from a KIPs perspective is process mining's abstraction from specific process instances for the sake of informing process re-design on a type level. Process discovery, in particular, is geared to identify standard operating procedures, while outliers are often filtered out. Process mining focuses on understanding and improving a process on a type level, to inform process analysts and developers on how they can re-design a process. At the same time, process mining's influence on specific process instances—i.e., single enactments of a process—remains difficult to determine [1]. Deviations in individual performances of KIPs—for instance, in a customer order process that is particularly tricky—cannot be adequately understood when analyses emphasize activity sequences and timestamps over context [18, 46, 47].

We posit that process mining of KIPs must ensure that tacit process-related knowledge is embedded into a process-specific knowledge base [20] that is leveraged to foster a culture of knowledge exchange and integration that is context-specific and informs process participants at run-time. Effectively mobilizing tacit process-related knowledge is essential not only for achieving KIPs' objectives [1] but also for enabling process mining to move beyond average-case analysis toward supporting context-specific decision-making. Moreover, KIPs concern not only activity execution but also the justification of actions, including reasoned deviations from norms [1]—an aspect traditional compliance checking perspectives neglect.

Moving beyond process mining's focus on analyzing operational processes, we posit that the SECI model can serve as a kernel theory to design process mining of KIPs. If organizations can manage their tacit process-related knowledge, this capability can open up a multitude of possibilities that increase their innovativeness and creativity [48]. Furthermore, knowledge provides a sustainable competitive advantage because, unlike material assets, it grows with use: ideas generate new ideas, and shared knowledge enriches both giver and receiver, enabling continual improvements in quality, creativity, and efficiency of an organization's processes and products [15]. Therefore, organizations must understand how managing knowledge impacts organizational structures and their governance [49].

3. Research Method

As a research paradigm, DSR addresses important organizational problems by developing innovative IT artifacts [50], while at the same time aiming for the abstraction of generalized theoretical knowledge in the form of type five theories for design and action [21, 23].

A concrete DSR research method that combines building and evaluation of IT artifacts, authentic organizational interventions, and the aim to generate design-oriented theory is ADR [24]. ADR comprises four phases: (1) problem formulation, (2) building, intervention, and evaluation (BIE), (3) reflection and learning, and (4) formalization of learning [24]. Each phase follows specific guidelines, acknowledging close collaboration between researchers and practitioners. The first three phases are reiterated until the "formalization of learning" phase concludes the ADR process. The BIE phase is an especially integrated phase in which building, intervention, and evaluation are intertwined and are therefore not always as distinguishable as with more stage-gate-like DSR methods [51]. The scientific core contribution of an ADR project is type five theory for design and action, for example condensed in design principles [22], which prescribe how a class of IT artifacts ought to be designed and how it can be instantiated in a similar context. Thus, the reusability of design principles is a critical characteristic that can be evaluated using five criteria, comprising (1) accessibility, (2) importance, (3) novelty and insightfulness, (4) actability and guidance, and (5) effectiveness [52].

In our ADR project, we performed three iterations, each comprising a BIE phase followed by a "reflection and learning" phase (see Figure 8 in the appendix). The content and the progression of each phase of the ADR study are depicted in Figure 2. The ADR team consisted of five researchers and five practitioners from three organizations. The practitioners were experienced members of the respective BPM or IT departments. Two of the mentioned organizations are manufacturers, one of which mass-produces industrial connectors (*Industrial Connectors Inc.*) and the other produces fluid separators (*Fluid Processing Ltd.*). The third organization is a software company (*Software Developing Inc.*) that offers product lifecycle and workflow management systems and is also the provider of these tools for *Industrial Connectors Inc.*. This software company supported the development and implementation of the software prototype in our project. Further details about the involved case organizations are summarized in Table 3 in the appendix. The close cooperation with the practitioners, as envisioned by ADR [24], enabled us to gain detailed insights into real-world KIPs at these organizations. At each case company, we selected one business process that met the criteria of a KIP, while ensuring coverage across diverse process characteristics such as structure, duration, and volume. At *Industrial Connectors Inc.*, we examined the product innovation process, which occurs roughly ten times per year but requires about a year to complete. Although it broadly follows a stage-gate model, it demands extensive engineering expertise alongside knowledge of marketing, certification, and production processes. Moreover, the process involves a wide range of roles and participants who contribute to the development of new products. At *Fluid Processing Ltd.*, we studied the engineer-to-order process in which machines—ranging from small devices to room-sized systems—are ordered and custom-designed. While components and modules can be reused, nearly every machine is unique and tailored to its specific use case, with significant implications for production, testing, and certification. Accommodating late-stage changes require highly specialized knowledge of both the domain and the individual machines to meet customer requirements. Both processes are strategic to the respective companies, as they represent core activities that either directly create value or form the basis for developing new products and maintaining competitiveness.

After three iterations, we conclude with an IT artifact coined *"process mining of KIPs"*, which provides explanations about a graphical user interface, its technical architecture, and, on an abstract level, we propose five theory-ingrained design principles on how to implement and use process mining of KIPs.

4. Process Mining of Knowledge-Intensive Processes

4.1. Problem Statement

We started the ADR process by defining the challenges of managing KIPs in our two case companies. To this end, we conducted management workshops to identify and understand relevant KIPs, including their activities, participants, and supporting information systems. We then performed 27 semi-structured in-depth interviews (40 hours in total) with process participants spanning operational staff to senior management. In parallel, we analyzed the relevant information systems—product lifecycle management (PLM), workflow management, and enterprise resource planning (ERP)—and their underlying data structures to assess the type, amount, and quality of available data, followed by an evaluation of their maturity for process mining [16, 53]. Overall, we conducted 49 workshops, cumulating to more than 125 hours of direct interaction with the case organizations. This approach enabled us to surface both technical and organizational challenges in applying process mining to their KIPs.

We complemented the empirical analysis of KIPs in our case companies with an in-depth investigation of the literature on KIPs and process mining. This analysis revealed that the challenges of applying process mining to KIPs are deeply intertwined with the very attributes of KIPs themselves (see problem statement phase in Figure 2). For instance, technical limitations such as limited data availability, fragmented event logs across ERP, PLM, and legacy systems, and inconsistencies in data quality (C2, C4) reflect the high variability and diverse control flows inherent in KIPs (A2). Similarly, the difficulty of predicting the progress of individual process instances (C1) [37] corresponds to their strong dependence on context (A6), which makes KIPs hard to standardize and digitize (A3). Moreover, human factors further amplify these issues. The lack of systematic knowledge storage (C3) and the dependency on individuals as knowledge bearers (C6), who often work in isolated groups and share insights only irregularly (C7), align with the human-centered and knowledge-intensive nature of KIPs (A1, A5). This also results in the existence of multiple versions of pieces of information, which can cause false assumptions (C5) [13]. Congruent to that, mistakes are often repeated because knowledge is not effectively shared (C8) [13]. In addition, knowledge development in KIPs often happens spontaneously and is tied to individual decisions within process instances (A4), making it even harder to capture, codify, and reuse with process mining.

From this integration of KIP-specific attributes and corresponding challenges, we derived four preliminary solution properties for a potential IT artifact. Such a solution must be able (SP1) to handle the high variability and complexity of KIPs, including their diverse control flows and fragmented data sources; (SP2) provide mechanisms to add codified, process-related knowledge directly in connection with process instances; (SP3) enable systematic storage and broad distribution of process-related knowledge; and (SP4) connect process participants across organizational silos to foster collaboration and knowledge sharing.

4.2. First ADR Iteration: Conceptual Development

4.2.1. Building, Intervention, and Evaluation

In the first iteration, we built a conceptual IT artifact of a tool that incorporates knowledge management capabilities and process mining techniques based on the described solution properties (see iteration 1 in Figure 2). In ADR, such an early-stage artifact is typically built and evaluated in close cooperation with the practitioners who are part of the core ADR team but is not yet presented to the end users [24].

The developed mock-up features two views, distinguishing between a process level and an instance level. The process level visualizes general information about the process and provides an overview of the running process instances and their states. The instance level provides information covering instance-specific process performance indicators (PPIs) and specific information on single activities (see SP3). To incorporate process-related knowledge, the artifact provides the possibility to upload important activity-related documents (see SP2). These documents should contain process-related information such as the justification of certain decisions or further details on the process. Since KIPs often have a unique structure (see SP1), specific process-related PPIs are shown. By considering the selected process properties and the defined goals, process instances similar to the analyzed case are identified, displayed,

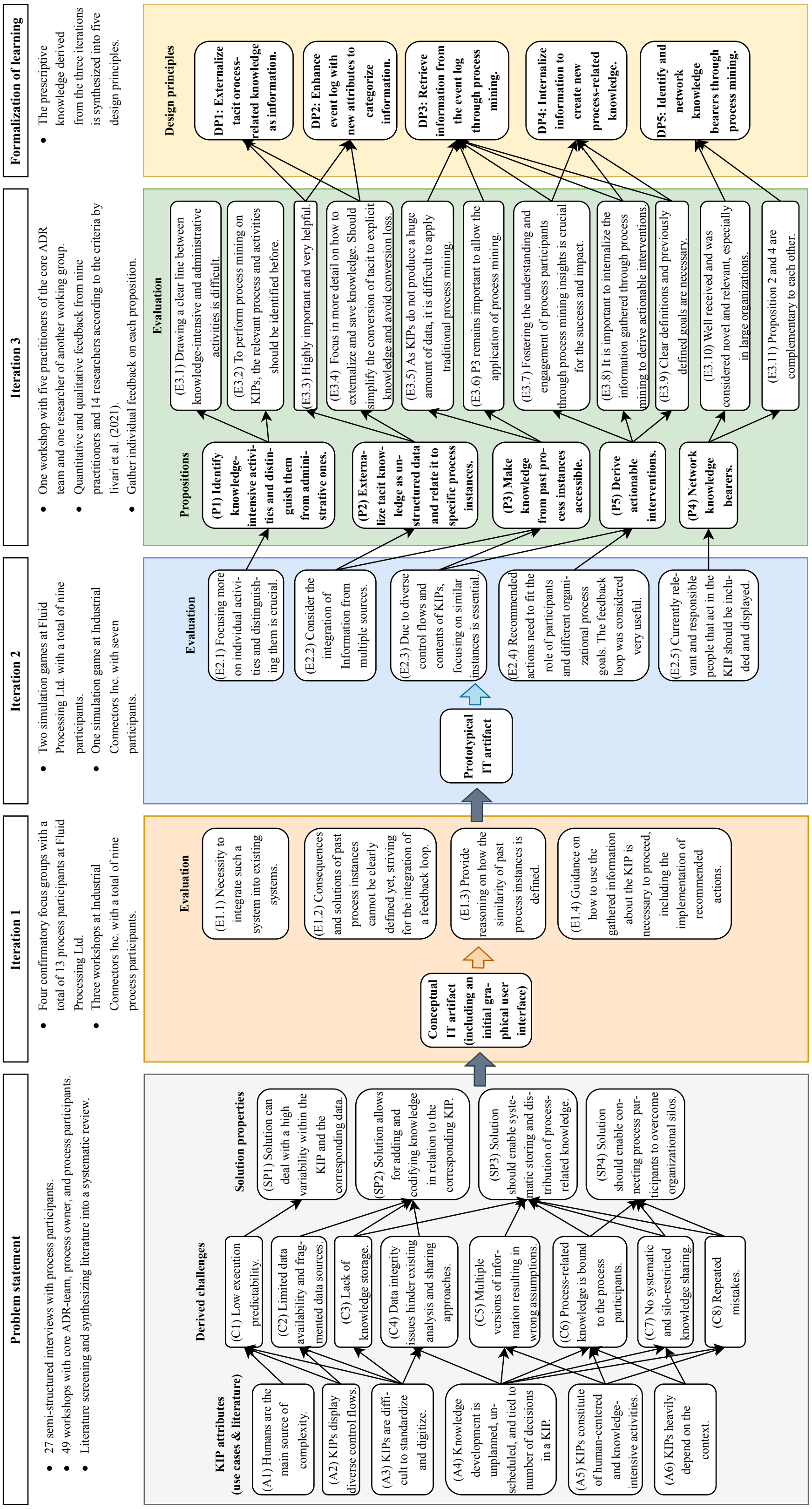


Figure 2: Comprehensive overview of the ADR study (incl. the results and feedback of each iteration)

and clustered. At this stage, the responsible process participants are already displayed, marking the first step toward connecting knowledge bearers (see SP4).

To evaluate the conceptual IT artifact, we conducted four confirmatory focus groups with *Fluid Processing Ltd.* and three with *Industrial Connectors Inc.* Each focus group took 90 minutes and resulted in feedback that informed us on how to refine the artifact (see appendix Table 4). In general, the conceptual IT artifact was assessed positively. The participants stated that such a tool would provide useful information and a good basis for communicating with other process participants and management if used correctly. It was emphasized that it is important not only to display process-related information but also to enable the possibility to add new knowledge. However, guidance was needed on how to enter new knowledge and how to interpret it to make strategic decisions in KIPs. Furthermore, the practitioners asked for the possibility of connecting multiple information systems as data sources.

> *"The underlying PLM does not provide all necessary information. For the tool to work, we would have to add our knowledge simultaneously. At best, this feature is well integrated and goes beyond adding simple files."* (Vice president of quality management at Industrial Connectors Inc.)

4.2.2. Reflection and Learning

The feedback from the focus groups provided valuable insights that resulted in minor and major learnings. Minor points contained the challenges of handling unstructured data and the difficulty of sustaining data quality if diverse process participants enter metadata for process instances. Additionally, we identified that the IT artifact must be integrated with existing information systems relevant to the KIP (E1.1). This is crucial to ensure the long-term commitment of process participants. We further learned that it is essential to identify and document historic strategic decisions made in KIPs, and to provide functionality for adding post-assessments of their consequences, thereby establishing a feedback loop (E1.2). For identifying similar past process instances, measuring the similarity should be context-sensitive. For example, in some cases, the used machine type can be decisive for identifying a similar process instance, whereas in other cases, the demands articulated by the customer are most important and must be taken into consideration to identify similar cases (E1.3). Finally, the practitioners asked us to provide detailed information on the actions taken and their effectiveness in the tool (E1.4).

4.3. Second ADR Iteration: Evaluating Utility

4.3.1. Building, Intervention, and Evaluation

Based on the learnings from the first iteration, we enhanced and implemented the conceptual IT artifact (see Figure 9-12 in the appendix and iteration 2 in Figure 2) by incorporating functionality for adding new process-related knowledge, to adjust the similarity of process instances dependent on the particular situation and goals, and for recommending actions with an integrated feedback loop. We used the expertise of the involved software provider *Software Developing Inc.* and implemented the prototype as a component of their existing workflow management system. The architecture consists of three layers (see Figure 13 in the appendix).

The data layer is responsible for extracting data from the source systems and preprocessing it to create a common event log. The processing layer consists of information retrieval and data analytics functionalities. The information retrieval components are responsible for processing the user input such as documents, decisions, and other unstructured forms of knowledge to enrich the event log. Furthermore, it reads from the enriched event log and is able to analyze the log with process mining techniques. Additionally, it is possible to calculate the similarity of individual traces and context-specific PPIs, as well as to process the additional unstructured information. The capabilities are expandable, e.g., the integration of large language models (LLMs) could be desirable for processing various knowledge sources and synthesizing them [54, 55, 56, 57]. The interaction layer is responsible for visualizing process-related knowledge and recommendations to the user, while also taking the user input such as decisions and documents.

Within the system, the user can examine the current progress of the selected process instance, enriched with instance-specific PPIs that provide additional context and guidance (see Figures 9-11 in the appendix). Moreover, the tool enables users to input documents, notes, and other files as explicit process-related knowledge. In our case, such inputs may include construction plans, business plans, unstructured notes, or material-related experiences. This information can be linked to specific tasks or associated with an entire process instance. Furthermore, users can add decisions and their justifications in an unstructured form to ongoing process instances or tasks (see Figure 10).

To validate whether the prototype supports process participants in their decision-making and execution of KIPs by making tacit process-related knowledge better accessible, we conducted an intervention. It comprised six workshops, including a simulation game with *Industrial Connectors Inc.* end users (two groups with a total of nine participants) and *Fluid Processing Ltd.* end users (one group with seven participants), adding up to more than 24 hours of direct interaction. During the first workshop, we introduced the business problem to be acted on in the simulation game and communicated the implemented design decisions and features of the IT artifact to prepare the participants for the simulation game. Subsequently, we simulated the respective KIPs due to their long lead times by observing process instances at specific moments, completing tasks, and fast-forwarding time (e.g., by three weeks) to simulate progress (see Figure 3). For each organization, four concrete evaluation scenarios were defined for managing KIPs based on real historical events.

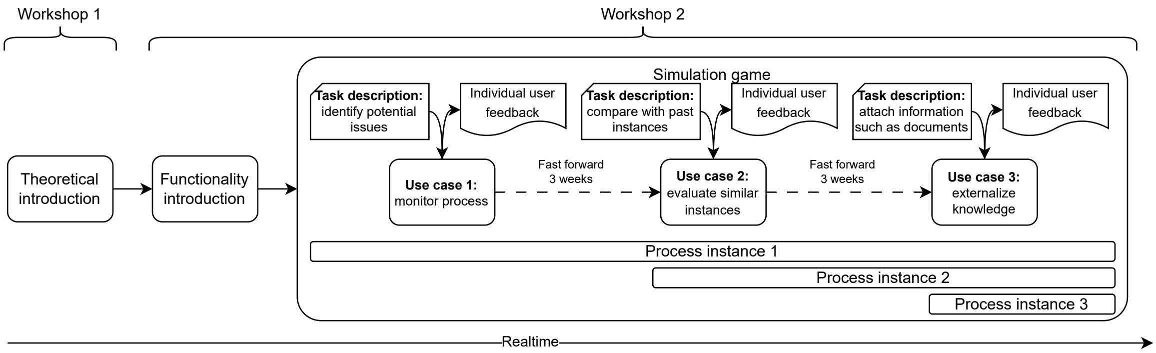


Figure 3: Visualization of the simulation game

After terminating the simulation game, we directly conducted a feedback session and distributed a survey to the participants to evaluate the prototype holistically (see appendix Table 5). The prototype's functions were classified as important and useful by both organizations, especially the possibility to view similar historic process instances. Participants from *Fluid Processing Ltd.* found the information presented in the prototype helpful, particularly for communicating strategic decisions to the management. However, they stated that not all required process-related knowledge was available, for example regarding individual activities in a process instance. *Industrial Connectors Inc.* communicated that it was still difficult for them to derive helpful knowledge about the KIP because of the high variety of activities, requiring very specific knowledge about a process instance.

4.3.2. Reflection and Learning

From interpreting the evaluation results of the second iteration, we gained insights on how to improve the accessibility of process-related knowledge. We obtained five major learnings. First, focusing on individual activities and distinguishing knowledge-intensive from administrative activities is needed to present activity-specific information (E2.1). Second, the system must be integrated with existing systems to ensure its usability and the availability of data (E2.2). Third, we reaffirmed that focusing on similar process instances, instead of analyzing all instances, was useful for mobilizing knowledge from past process instances for managing KIPs (E2.3). Fourth, recommended actions should be tailored to the role and goals of the active process participant, and a feedback loop must be supported to evaluate the effectiveness of past decisions and actions (E2.4). Fifth, relevant and responsible process participants that act in the KIP should be included and displayed to allow the active user to reach out to a knowledge bearer through socialization for more detailed information (E2.5).

4.4. Third ADR Iteration: Ensuring Reusability

4.4.1. Building, Intervention, and Evaluation of Propositions

Based on the learnings from iteration two, we sketched five propositions to refine them in an internal and external validation step for reusability [52]. The five propositions (see iteration 3 in Figure 2) comprise (P1) the identification and differentiation of knowledge-intensive and administrative activities, (P2) the enhancement of the event log with externalized process-related knowledge, (P3) the retrieval and combination of knowledge from similar past process instances, (P4) the identification and networking of knowledge bearers within the processes, and (P5) the derivation of actionable interventions with the possibility to provide reasoning on decisions to evaluate past decisions' effects on process goals.

The internal evaluation involved the core ADR team. We first presented the developed propositions before we conducted a feedback session in which the participants had the opportunity to provide qualitative feedback on each proposition (see appendix Table 6). Subsequently, we conducted an evaluation with external practitioners and researchers to ensure further external validity. In total, we completed 17 workshops with 23 different participants (nine practitioners and 14 researchers). Each workshop included a short introduction and explanation of the propositions, employing the elements described by Gregor et al. [22]. The participants were then asked to give quantitative (see appendix Table 7) and qualitative (see online appendix[1]) feedback on each proposition. For the quantitative external evaluation, we used a 5-level Likert scale.

Whereas the practitioners classified the propositions in general as too abstract, the researchers valued their flexibility. An in-depth analysis of the quantitative feedback showed a generally positive assessment (see appendix Table 7), with the factors accessibility and effectiveness reaching high scores, while the factors actability and guidance received mixed reviews, especially for propositions 1 and 3.

While the participants understood the basic idea behind proposition 1, they mentioned that drawing a clear line between knowledge-intensive and administrative activities is difficult (E3.1). Instead, they argued that the relevant KIP must be identified in the first place, which is a challenge in itself (E3.2). Moreover, several researchers and practitioners highlighted that differentiating between activities can already provide insights into the structure of the process and foster reflection.

Proposition 2 was highlighted as very important and helpful for any kind of process analysis (E3.3). However, this proposition was identified as a significant challenge due to the complexities involved in transforming tacit into explicit process-related knowledge. This transformation is associated with a corresponding conversion loss (E3.4). Another relevant challenge is the willingness of the process participants to share their process-related knowledge because giving it away to others could have the negative effect of making them obsolete.

> *"Employees may not want to share their knowledge at all due to competitive thinking and whatever else is involved."* (P6)

During the internal evaluation, participants from *Fluid Processing Ltd.* supported proposition 2, noting that they already asked other process participants to attach relevant documents to their ERP system.

Proposition 3 was perceived as mandatory (E3.6). However, measuring the similarity of process instances is challenging and probably subject to different process goals. This is further reflected in its low score on actability and guidance. Moreover, it was stated that KIPs do not produce huge amounts of data; therefore, applying traditional process mining techniques will probably be difficult (E3.5).

Most of the participants agreed with proposition 4 and highlighted its novelty (E3.10), while also mentioning possible trust issues and the impact of organizational culture on the willingness of the process participants to share their process-related knowledge.

> *"Especially in knowledge-intensive processes with specific instances, many different cases exist. If networking employees is also used for a process instance, I think that brings a lot of added value."* (R13)

Particularly, in the quantitative feedback, proposition 5 received a relatively low score on novelty and insightfulness, and it was not clear whether the actions were targeted at the process as a whole or at single process instances. Furthermore, some researchers warned about the term "prescriptive" because solely finding a proper action is already difficult, and there might be the hazard of wrong prescriptions. Regarding actability, several interviewees explained that it would be a particularly challenging proposition to implement.

4.4.2. Reflection and Learning

Based on the feedback from the internal and external evaluation workshops, we revised and transformed the propositions into design principles [22]. For proposition 1, we observed that the differentiation between knowledge-intensive and administrative activities provides valuable insights into the process structure and raises awareness among stakeholders but is challenging to implement. We observed that identifying relevant processes and drawing clear distinctions is inherently difficult but should be considered as a prerequisite. Regarding proposition 2, we

[1] Iteration 3: Qualitative External Feedback

learned that it is a critical step for effective process analysis. However, the concept of converting tacit process-related knowledge into explicit process-related knowledge needs to be strengthened. From the feedback regarding proposition 3, we learned that focusing on similar past process instances remains important, but the local data quality, independent from the information added by following proposition 2, remains a challenge (E3.5). Proposition 4 seems particularly valuable in large organizations where process participants may not know each other. However, we observed concerns about trust and rivalry. To improve actability, techniques like social network analysis might be used. These insights regarding proposition 4 emphasized a complementarity with proposition 2 (E3.11). The feedback concerning proposition 5 showed a need for clear definitions and upfront goal-setting to avoid ambiguity and guide actionable recommendations effectively to mitigate the risk of incorrect prescriptions (E3.9). Additionally, fostering process participants' understanding and engagement through process mining insights is crucial for the successful implementation of and positive impact on strategic decisions (E3.7). However, to take action, process participants are required to internalize the information gathered through process mining (E3.8).

5. Formalization of Results

Based on our learnings from the three iterations (see Figure 2), we condensed the prescriptive knowledge gained into five design principles [22] that prescribe a new class of IT artifacts coined "*process mining of KIPs*". The design principles bridge practice and theory by capturing mechanisms and contextual factors for successful artifact design and use. They provide reusable type five theory for design and action [21, 23] for researchers and practitioners. The design principles draw on the literature of knowledge management, especially the SECI model [20], and process mining [16, 17], as well as the insights gained from the case organizations. The mutually interdependent design principles explicitly address the mobilization of knowledge by supporting the conversion of tacit into explicit knowledge and vice versa, building on the modes of socialization, externalization, combination, and internalization [20]. Figure 4 illustrates how the design principles are informed by the kernel theory. The proposed mechanisms reach beyond the current confinements of process mining as a tool limited to analyzing explicit knowledge captured in event logs. Table 1 provides an overview of each design principle in line with Gregor et al. [22], presenting the aim, implementer & user, the mechanism, and the rationale. In doing so, we defined three different roles that are addressed in the design principles. These roles comprise the IT artifact, a process analyst, and process participants [40, p. 24–26]. In the following, each design principle is explained in detail.

5.1. DP1 (Externalization): Externalize Tacit Process-Related Knowledge to Information

The process of externalizing tacit knowledge is rooted in the SECI model [20] where employees try to describe knowledge that would otherwise remain hidden. Humans are the main knowledge bearers in organizations, implying that a large amount of knowledge is often not codified but remains tacit [20, 5]. This is particularly true for KIPs that are highly dependent on the creativity and experience of skilled process participants [1, 10, 2, 11]. Thus, transforming tacit knowledge into explicit information that can be shared with and accessed by others to build on this information and create new knowledge is critical [43]. Knowledge can be transformed into explicit information by expressing it using words, images, text, etc. [7]. In our study, we observed that even though organizations are aware of that fact and of the problems that not transforming knowledge into information might cause, no sufficient mechanism is in place to convert tacit process-related knowledge into explicit information.

To enable the conversion of tacit process-related knowledge into explicit information that can be accessed by others—including humans and information systems—the IT artifact needs to enable process participants to add their process-related knowledge as unstructured information to the artifact. Hence, an IT artifact needs to provide an input mask that allows process participants to add their process-related knowledge in a textual form or as an attachment (e.g., documents, drawings). To ensure that each knowledge contribution is linked to the corresponding process instance and activity, the input mask must provide functionality (e.g., a selection button or dropdown menu) that allows process participants to specify the activity to which their contribution relates. This ensures that the unstructured information is contextualized and retrievable when applying process mining analysis techniques.

5.2. DP2 (Combination): Enhance Event Log with New Attributes to Categorize Information

While unstructured data often carry a high implicit value in themselves, they can hardly be analyzed efficiently and in a goal-oriented manner. Furthermore, unstructured data are often not stored in event logs, despite having the potential to provide useful insights and improve contextualization [58]. Most algorithms for analyzing unstructured

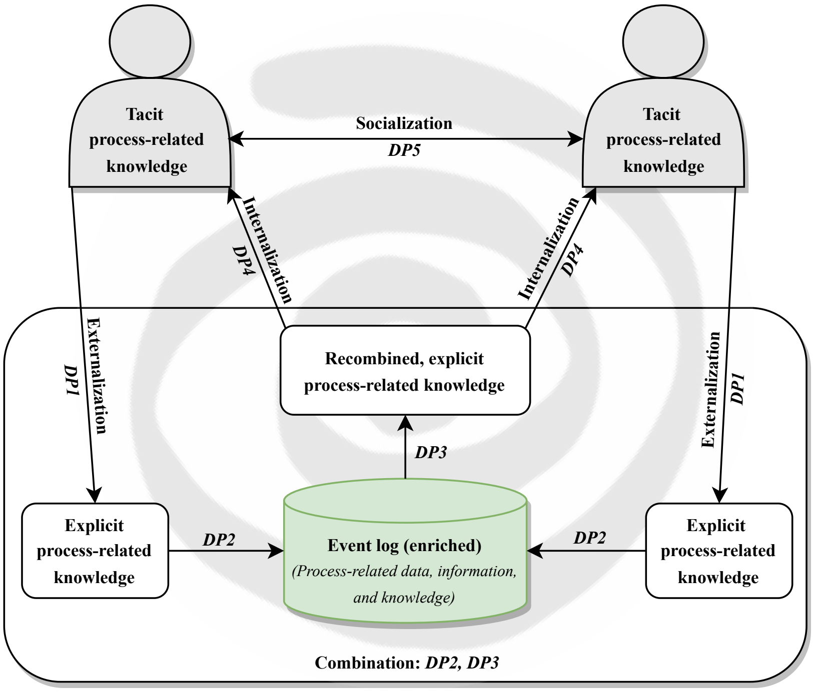


Figure 4: Conceptual link between SECI model and design principles for process mining of KIPs

data build associations and search for correlations. However, one problem is that the results are often not explainable, which has drawbacks when decisions cannot be made solely on analysis results alone but need to be interpreted and justified in a decision-making process.

To enable process mining of KIPs, information must first be converted into data and systematically stored in the event log. The event log already captures process-related data and explicit knowledge about the process, assigned to specific process instances. Storing additional information as structured data requires categorizing and classifying it before it can be assigned to a process instance in the log as an attribute. This implies not only transforming information into single data entries but also defining categories that are both machine-readable and human-interpretable. Consequently, the event log schema must be extended beyond its typical attributes (e.g., case ID, activity, timestamp) to include new attributes representing the contributed process-related information, as well as references to attachments such as documents or drawings. Since these contributions are already linked to case IDs and activities at the instance level (via DP1), they can be directly integrated into the log. This integration allows process mining techniques not only to analyze behavioral data but also to contextualize events with relevant process-related knowledge, thereby improving interpretability and supporting better-informed decision-making.

5.3. DP3 (Combination): Retrieve Information from the Event Log through Process Mining

Decision-making in and performance of knowledge-intensive activities by process participants are biased by what seminal work by Tversky and Kahneman [60] coined availability heuristics. These heuristics describe the fact that people are systematically biased in their ability to recall specific events and to judge the representativeness of the recalled events by their subjective experience. Thus, combining explicit knowledge from different sources to make it available is essential [20, 43]. In our study, we found that only a few process participants with high experience were able to recall similar past events to inform their decisions and actions in a running process instance.

Because humans are biased in recalling past events, presenting them with information (including descriptive, diagnostic, predictive, and prescriptive information) on related historical events can help overcome the systematic bias in their judgment and performance of process activities. As KIPs have a high variance in their structure [1], information about similar instances of past processes should be made available. Identifying these similar process instances from the past can, for example, be achieved by applying trace clustering [59]. Hence, information about similar past process

Design principle 1 (externalization): Externalize tacit process-related knowledge as information	
Implementer	Process participant
User	IT artifact & process analyst
Aim	To externalize a process participants' 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 [20], especially in knowledge-intensive processes reliant on skilled participants [1, 10, 2, 11]. 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 them 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 [58]. 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 to information by retrieving information of past process instances from the event log.
Mechanism	Identify similar past process instances (e.g., through trace clustering [59]). 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 [60]. Combining explicit knowledge from diverse sources is essential [20, 43], 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 [20, 43]. 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 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 [61, 20, 43], 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 1
Design principles for process mining of KIPs, using the schema proposed by Gregor et al. [22]

instances has to be retrieved by integrating and processing data about these instances from the event log and presenting it to process participants in an easily accessible way. Thereby, it is important to add information that explains the reasons why the presented past process instances are identified as similar to the running instance. In doing so, existing process mining methods need to be extended through new techniques that can not only process structured data but also unstructured data in textual or even visual representations (e.g., through the integration of LLMs, computer vision, etc.) [54, 62]. Thereby, it is important to especially consider predictive and action-oriented process mining techniques [17], because information generated through these techniques can support process participants in making decisions and in executing running and new process activities and process instances. For further improvements, it is important to clearly state the effect of the actions taken based on the provided information and to integrate a feedback loop so that the artifact can learn further.

5.4. DP4 (Internalization): Internalize Information to Create new Process-Related Knowledge

The knowledge creation process describes that new tacit knowledge is created by internalization [20]. Internalization describes the activity in which humans relate information to their experiences and beliefs and create new knowledge that is implicitly available to them [20, 43], closely related to *learning by doing* [43]. Information is transformed into knowledge after it has been processed in people's minds [7]. In our study, we observed that information that is presented to process participants when carrying out tasks in business processes determines their task performance.

Consequently, in the context of KIPs, an IT artifact needs to present process participants with information that is useful to their specific context and situation (i.e., the process instance they are currently working in). The presentation of relevant process-related information (e.g., through the interaction layer) enables process participants to internalize information and create knowledge to increase their ability to perform an instance of a KIP and take action.

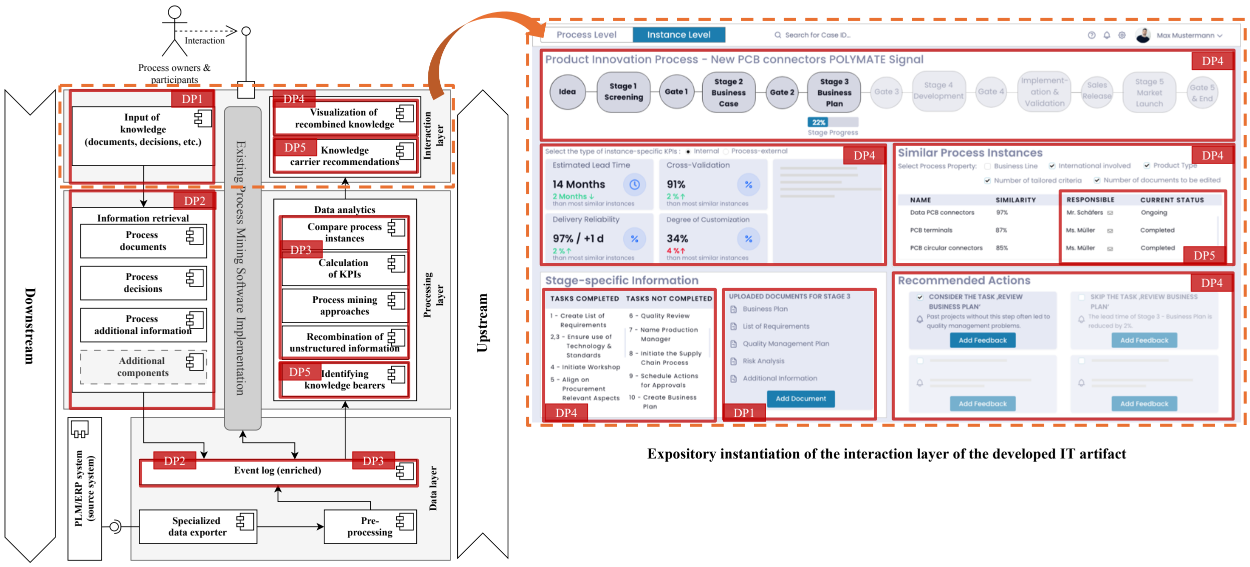
5.5. DP5 (Socialization): Identify and Network Knowledge Bearers through Process Mining

Individual knowledge cannot contribute to the organizational knowledge base if it is not shared among individuals [61]. Through socialization, employees learn from each other and share their experiences and individual knowledge, enriching the organizational knowledge base [20, 43]. However, concerning the availability and distribution of knowledge, employees who are knowledge bearers often remain hidden and cannot be easily identified. This fact makes it difficult to access their individual knowledge and learn from each other. In our study, we observed that for most challenges that occurred in the KIPs, process participants with high experience and knowledge from past, similar process instances existed, but they were neither known nor identifiable by others.

By applying process mining to KIPs, knowledge bearers can be identified, and process participants can connect and interact with them. This is enabled by a drill-down mechanism that becomes available because other knowledge bearers have already added their knowledge as information to the artifact before it was transformed and recombined for the currently requesting process participant. Thus, the knowledge transformation process can be uncovered by the IT artifact following a "reverse engineering" approach. By leveraging approaches such as organizational mining [17] and discovering social networks from event logs [63], knowledge can be traced back to the process participant who initially entered the information related to an identified similar process instance in the past.

5.6. Expository Instantiation of an IT Artifact Building on the Design Principles

The manifestation of the design principles in the instantiated IT artifact is depicted in Figure 5: DP1 and DP4 relate to the interaction layer, DP2 and DP3 to the processing and data layer, and DP5 spans the interaction and processing layers. DP1 is implemented by allowing process participants to upload relevant documents (e.g., modification masters at *Fluid Processing Ltd.* or part numbers at *Industrial Connectors Inc.*) and to attach tacit process-related knowledge directly to tasks within a process instance (see also Figure 10 in the appendix). DP2 describes how the newly added process-related information (processing layer) is processed as data and how the event log is extended with new attributes for the categorization of information (data layer), while DP3 enables retrieving (data layer) and combining (processing layer) enriched information from the event log. DP4 is instantiated to provide participants with contextualized information in the interaction layer, such as the current state of the process instance, PPIs, and insights from similar past cases. Similar past process instances are identified, displayed, and clustered by enabling process participants to consider process properties and define goals. This helps participants internalize information, generate knowledge, and act effectively. Additionally, the artifact recommends actions on how to proceed in the process, based on the identified similar instances, and enables process participants to evaluate them to refine the system further. DP5 supports identifying and networking knowledge bearers by retrieving relevant actors from the event log (processing layer) and displaying them to users (interaction layer), thereby fostering knowledge exchange.



Layered architecture of the developed IT artifact

Expository instantiation of the interaction layer of the developed IT artifact

Figure 5: Manifestation of design principles in the instantiated IT artifact

6. Discussion

Our design principles make an important contribution towards advancing process mining into a method for managing KIPs as strategic processes in organizations, reaching substantially beyond its current confinements to the event logs of operational processes (see Table 2). We posit that our design principles enable an organization to generate process-related knowledge about KIPs that refer to epistemological and ontological dimensions of organizational knowledge creation [20]. The epistemological dimension focuses on how knowledge can be created and how the knowledge-creation process is managed. Central to this view are the four modes of knowledge conversion. The ontological dimension focuses on how organizations can implement structures that convert individual knowledge into collective assets on a group level or organizational level. Central to this view is the spiral of organizational knowledge creation, visualizing how knowledge moves cyclically between individuals and organizations. By addressing both perspectives, our process mining approach facilitates generating process-related knowledge about KIPs (epistemological perspective) and distributing it from individuals to organizations and back again (ontological perspective) [20].

6.1. Process Mining of KIPs from an Epistemological Perspective

In the SECI model, the conversion between tacit and explicit knowledge occurs through the four modes of socialization, externalization, combination, and internalization [20]. Our design principles build on these modes and detail them as guidelines for establishing process mining as a tool for analyzing and managing KIPs (see Figure 6). The knowledge creation process enabled by these mechanisms operates differently than the knowledge creation process for operational processes as enabled by current process mining approaches (see Figure 1).

The first design principle for externalizing tacit process-related knowledge into information is based on the externalization mode [20, 43], converting tacit process-related knowledge into explicit process-related information. Current IT artifacts primarily handle codified, explicit organizational knowledge [7]. This observation also applies to process mining, focusing on event logs as data sources [17, 18]. We argue that integrating knowledge management capabilities into process mining, as proposed in DP1, enables organizations to access richer forms of knowledge, such as process participants' tacit knowledge about specific instances of a KIP [7].

DP2 and DP3 enhance event logs with additional categorized information and enable the retrieval of information from an extended event log. Previous research has often overlooked the opportunity to include unstructured domain data in event logs, although these data are argued to provide useful insights and improve contextualization [58]. Classic data

Concept	Current process mining approaches	Process mining of KIPs
Primary type of business process analyzed	Standardized, repetitive, digital business processes	Knowledge-intensive, context-sensitive strategic core processes
Primary type of externalized knowledge	Case ID, activities, control flow (directly-follows relationships), resources, time stamps, all stored in an event log as the primary artifact	Beyond a classic event log: filled templates, documents, orders, drawings, slides, and other types of unstructured data
Primary focus of the analysis	Focus on internal quality criteria, e.g., control flow, bottlenecks, resource consumption, cost, time	Focus on external quality criteria, e.g., customer satisfaction, value co-creation, adaptability, exception handling, solution-orientation
Primary unit of analysis	Processes on an instance level, analyzed to identify processes on a type level	Processes on an instance level, analyzed to inform processes on an instance level
Primary mode of analysis	Data-driven analysis of the entire dataset across all process instances, abstracting from outliers to identify standard variants of a business process	Similarity among a few closely related process instances, while abstracting from all other process instances
Primary user of the system	Process analyst	Process participant
Primary purpose	Process re-design on a type level, to stimulate process excellence on an instance level	Excellence on a process instance level
Primary socialization activity stimulated	Process analysts and process participants to cooperate on process re-design	Process participants to cooperate with each other on performing their own KIPs

Table 2
Current process mining of operational processes vs. process mining of KIPs

fields in event logs include case ID, activities, and timestamps, making process mining best applicable to processes in which direct-follows relationships and time are paramount. In KIPs, however, external criteria such as customer satisfaction are more important than maximizing process efficiency. We posit that additional data fields should be included in the eXtensible Event Stream (XES) standard, which standardizes a language for exchanging, storing, and transporting process event data [64]. Further implications relate to updating the maturity levels of event logs that are currently focusing on classic data fields [16].

To make use of the additional data types, existing process mining methods need to be extended through new methods that can process not only structured data but also unstructured data in textual or even visual representations (e.g., natural language processing, computer vision, etc.). First studies have already conducted research on extending process mining through new techniques and applied approaches, such as Bidirectional Encoder Representations from Transformers (BERT) or LLMs, to handle textual data [37, 54, 55, 56, 57]. Including knowledge creation capabilities into existing technologies [4] (here process mining), is essential because social actors take a while to transform data into information [39]. With the new class of IT artifacts coined "*process mining of KIPs*", it is possible to analyze data [4] and stimulate the (re-)combination of data to information (see DP3), so that process participants can create knowledge through the internalization of new information (see DP4). The implementation of DP2 and DP3 enables organizations to present process participants with information on related historical events that can help overcome the systematic bias in their judgment and performance of process activities. Importantly, this refers to a selection of similar instances that is "just right", favoring similar instances over huge datasets of unrelated process instances [65]. Building on the concepts of adaptive case management (as already used in the healthcare domain), knowledge and information about KIPs can be stored to inform the management of similar process instances in the future [33, 66].

According to Bhatt [39], the best way to transform information into knowledge is through social actors. Therefore, our approach foregrounds participants who actually perform processes in their day-to-day work as users of process mining, following the idea of action-oriented process mining [17, 67]. New knowledge can be created through the reconfiguration of existing information by sorting, adding, combining, and categorizing explicit knowledge [20]. This enhances process participants' tacit knowledge related to a KIP by assisting them in internalizing what they have experienced [20]. Therefore, DP4 is rooted in the mode of internalization [20, 43]. Whereas information technology is effective at converting data into information, it is not a good substitute for turning information into knowledge; instead, it can only support process participants in internalizing new knowledge [39].

Traditional process mining focuses on process analysts as users so that they can re-design processes that are then executed by process participants [68]. Our approach, however, aims to present process participants with relevant information that is immediately related to the process instance they currently perform. This immediate action-ability

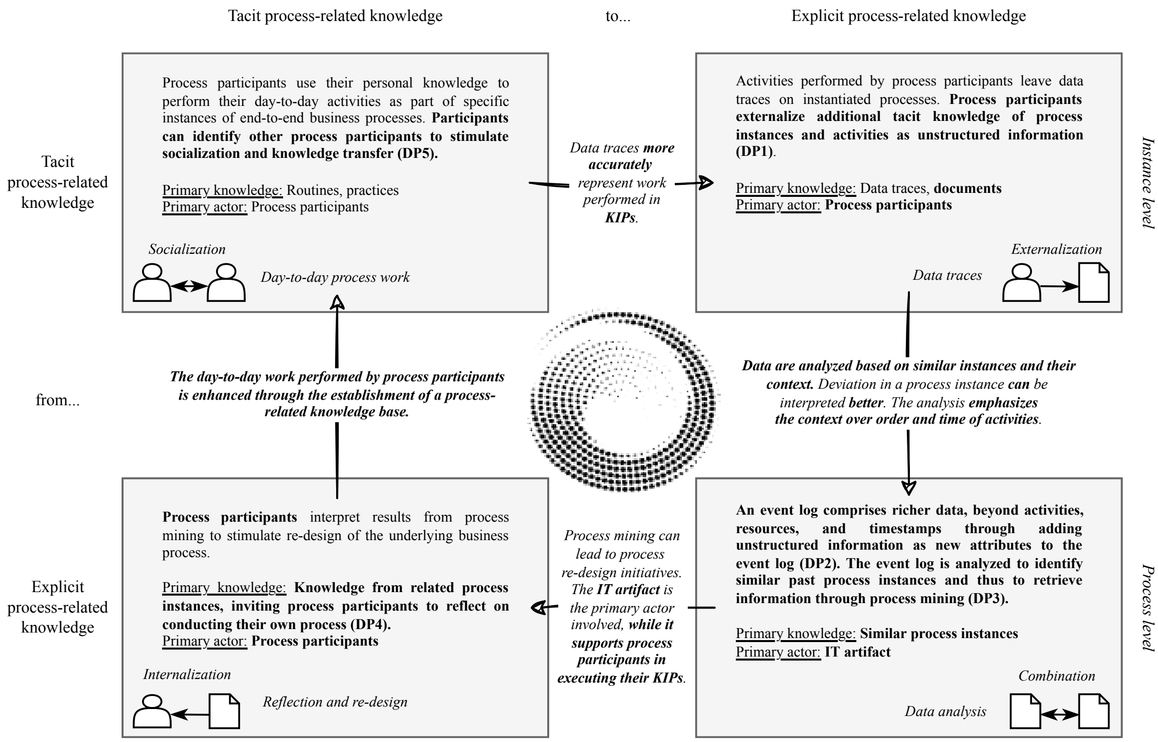


Figure 6: Process mining of organizational knowledge creation in KIPs[1]

[1]Impact of design principles and changes in comparison to Figure 1 are highlighted in bold

affects not only the visual representation of information but also the question of which information is made available to whom and when. Additionally, it might be beneficial to integrate LLMs into a process mining tool so that process participants can ask for information regarding their process instance or a specific activity. While current research is still evolving, LLMs show potential to process event logs and textual information in ways that may support the capture and distribution of relevant information and knowledge regarding KIPs [62, 54].

DP5 aims at networking process experts in an organization and is driven by the mode of socialization [20, 43]. By implementing this design principle, experts can be identified and connected to interact with each other. Socialization is particularly important because new knowledge in organizations arises from productive dialogue [69], such as dialogue on KIPs. Rooting in social network theory, the expansion of an individual's network with more relationships, though potentially weaker, is a pivotal aspect of the knowledge diffusion process [70]. Social networks facilitate exposure to a greater diversity of ideas, enhancing the potential for knowledge acquisition and innovation [70]. Thus, the access to and dissemination of information and knowledge among process participants can bring new perspectives [61]. To facilitate the transfer of knowledge, information technology can be used to allow individuals to extend their reach beyond the boundaries of formal communication channels [7]. At the same time, the search for knowledge sources is often constrained to direct colleagues with whom the individual has regular and routine contact [7]. To build knowledge networks, the concept of organizational mining can be adopted and integrated into process mining, which builds on the resource perspective of a process [17]. The goal of organizational mining is to discover and analyze social networks, revealing how resources have collaborated to execute individual process instances [17]. Collaborations of different resources can be visualized as social network graphs, in which the nodes represent the resources and the arcs represent the form of collaboration between pairs of resources [63]. In an event log of a KIP, information about participants performing an activity can be documented, thereby exposing the social network behind each process instance and creating a knowledge network surrounding the KIP. This information can help process participants identify other experts with whom they can socialize to acquire new knowledge.

6.2. Process Mining of KIPs from an Ontological Perspective

Because organizations are unable to create knowledge themselves at an abstract level, knowledge created at an individual level must be amplified and crystallized to become collective assets at an organizational level [20]. Thus, before knowledge can be utilized at the organizational level, it must be distributed and shared throughout the organization [39]. This process is conceptualized by the spiral of organizational knowledge creation, developed by Nonaka and Takeuchi [20]. The way that people, organizational technologies, and techniques interact affects if and how knowledge is distributed [39]. Therefore, it is a crucial task for management to support the ontological dimension that enables the transformation of individual knowledge into group or organizational knowledge, and back again [20]. Still, identifying knowledge, making it accessible to other employees, and combining it remain major challenges to creating new organizational knowledge [71].

Our results demonstrate that, in the context of KIPs, it is important to go beyond approaches that manage processes and process-related knowledge separately [19, 72]. Organizations must integrate BPM with knowledge management capabilities [73]. By developing our design principles as concrete mechanisms that extend the SECI model, we adapted the theory of organizational knowledge creation to the field of BPM, enabling the conversion of knowledge among process participants and generating process-related knowledge about KIPs. Our evaluation shows that the expository IT artifact supports a knowledge-creation process in KIPs that differs significantly from the knowledge creation fostered by current process mining approaches. Thus, we not only enable organizations to make tacit knowledge related to a KIP explicit but also propose new ways of creating organizational knowledge.

Figure 7 illustrates how our approach supports the ontological perspective by embedding the design principles into the spiral of organizational knowledge creation [20]. The figure adapts the original spiral by integrating a process-related knowledge perspective, thereby framing it through a process lens (as highlighted in bold in Figure 7). Since the SECI model operates at the individual level, the y-axis represents the epistemological dimension, which is essentially its core principle. By introducing the ontological dimension on the x-axis, we extend this view beyond the process-related knowledge level of process participants toward higher levels of knowledge development. Knowledge exchange no longer occurs only at the level of individual process participants, but—when driven by our design principles—extends further, crystallizing process-related knowledge to higher ontological dimensions (see x-axis in Figure 7). Continuously initiating new cycles of knowledge creation with our approach enables the creation of knowledge related to a KIP in a spiral process that starts with individual process participants, progressing from specific process instances to the process type level.

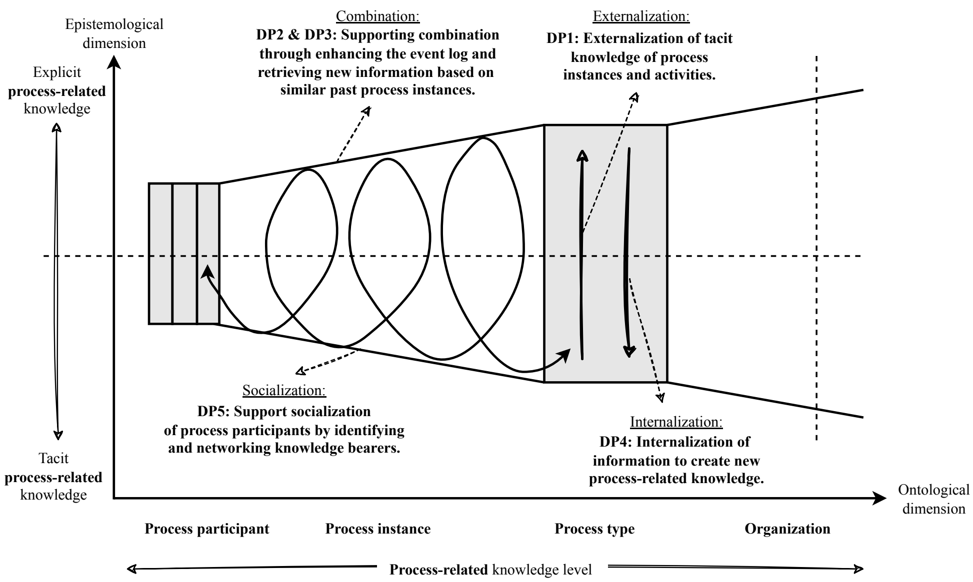


Figure 7: Supporting the ontological dimension with process mining of KIPs[1]

[1]Adaptations from the original figure [20] are highlighted in bold

As a result, a well-developed knowledge base about a KIP can be established, which can then be used to adapt and improve the process, based on a growing amount of data and available information [72]. This is important because managing knowledge serves as the foundation for effective process management, adjustment, and implementation [72]. Nevertheless, to capitalize on knowledge, an organization must balance its knowledge management activities subject to changes in organizational culture, technologies, and techniques [39]. Thus, organizations need to foster a culture of knowledge exchange [20] and trust to mitigate rivalry among process participants so that they are willing to share their knowledge, which is an essential component for the successful implementation of the design principles.

While information technology is limited in interpreting data and information, it can quickly capture, store, and distribute them [39]. Focusing on process mining as a technology helps align an organization's process and knowledge management activities [73] and capitalize on the growing amount of process-related data [17]. Vice versa, if this database is not effectively analyzed and managed, the complexity of the business process will continue to increase, which might have adverse consequences for an organization.

7. Conclusion, Limitations, and Outlook

In this paper, we prescribe a new class of IT artifacts coined "*process mining of KIPs*" through five theory-ingrained design principles. These design principles were developed in an ADR project with two case organizations and one technology provider. They propose to integrate richer process-related information into event logs, allow process participants to learn from similar process instances, and engage in socialization. These results contribute to the research streams on process mining and knowledge management. In contrast to process mining of operational processes, which identifies data from all process instances to support process management and redesign on a type level, our approach enables the mobilization and conversion of an individual's tacit knowledge about a KIP and the conversion of this knowledge to a higher ontological level. In doing so, a process-related knowledge base for KIPs can be established.

The new class of IT artifacts directly addresses existing challenges of managing KIPs due to their reliance on tacit knowledge, fragmented information, and the limited applicability of traditional process mining. By extending process mining with the developed design principles, we provide organizations with mechanisms to systematically capture, share, and reuse process-related knowledge. This new approach helps overcome current barriers and supports more informed strategic decision-making in knowledge-intensive contexts.

While our study makes theoretical and practical contributions, it is also subject to limitations. The development and evaluation of our approach were constrained by the experiences of the case organizations involved in the ADR study. The selected cases (product innovation and engineer-to-order) are representative of KIPs but do not capture the full diversity of contexts (e.g., healthcare, consulting, public administration). Although the utility of the approach was demonstrated in the participating organizations, we were unable to evaluate its longitudinal effects or large-scale organizational adoption. Integrating the artifact into existing IT landscapes also proved complex and was only partially addressed. Further, we acknowledge that data quality and preparation are critical aspects in process mining projects. For the purpose of our study, we assumed the availability of an event log of the KIP as the starting point for applying and evaluating our artifact. Accordingly, we did not explicitly address the preconditions or data-related requirements within the design principles themselves. These are part of subsequent research to enable the effective use of the proposed design principles. Moreover, while internal and external evaluations ensured the validity and reusability of the design principles, their application in other organizations may lead to further refinement. Additionally, our study did not explicitly investigate the willingness of process participants to contribute their process-related knowledge actively. Finally, given the ADR setting, the researchers' strong involvement in the context may have introduced bias into both design and evaluation. These limitations, at the same time, open avenues for future research to validate, extend, and refine the proposed design principles across different contexts, and to study cultural antecedents that foster knowledge sharing.

A. Appendix

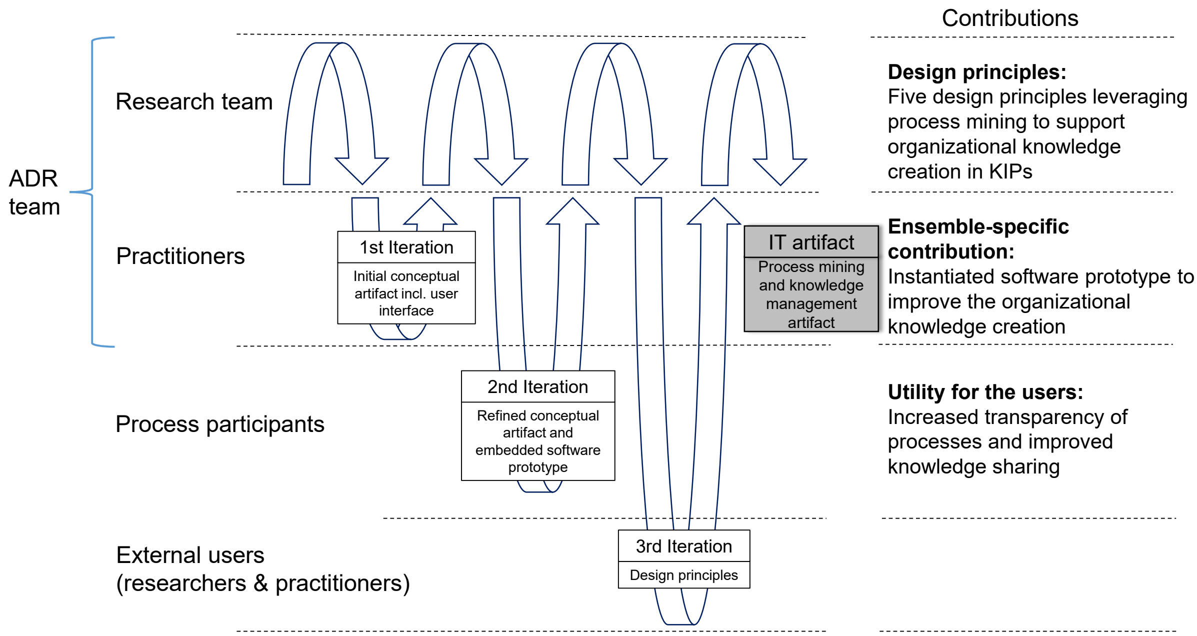


Figure 8: Action Design Research process

	Industrial Connectors Inc.	Fluid Processing Ltd.
Process	Product innovation process	Engineer-to-order process
Process Model	Individual process instance adaptations by the project manager.	Control flow varies based on machine type and customer requests.
Involved organizational Units / Roles	head of business unit, product manager, project manager, project engineer, product developer, controlling, procurement, quality management	product manager, product engineer, supply chain management, mechanical engineering, production unit, quality management, sales and distribution, external service provider
Process Tasks	Knowledge driven and variable process tasks. Only few non-knowledge-driven tasks. Mostly engineering and planning tasks.	Variable and knowledge intensive treatment of post production changes. Many non-knowledge-driven tasks for handling the instances. Primarily engineering and production tasks.
Knowledge Artifacts	Engineering document, environment, health & safety documents, financial plannings, and more	Engineering documents, production schedule, quality reports, and more
System Support	PLM system as BPM system.	No distinct BPM system. ERP system orchestrates parts of the process.
Yearly Instances	Ten instances	700 instances, of which 350 instances include changes
Typical Duration	12 months typical duration	6-7 months typical duration
Industry & Products	Electrical connectors for industrial purposes	Centrifuges and separation equipment for a broad range of industries
Size	650 employees local, 4,700 worldwide	1,900 employees local, 18,000 worldwide
Revenue (2022)	1.175 billion euros	5.3 billion euros
Involvement	First and second iteration	First and second iteration

Table 3
Overview of case organizations and processes

Feedback Fluid Processing Ltd.	Feedback Industrial Connectors Inc.
• The tool should also be extended to other departments and processes for consistent transparency (e.g., reduction in phone calls and mails, support of communication). • It is important to improve the data basis. What is currently visible in the system does not correspond to reality. The added value of such a system only becomes visible when the data basis is correct. • Positive feedback regarding the presentation of changes and their reasons in the process so that conclusions can be drawn for follow-up projects. • Responsibilities should be defined at the individual stages of the process. • For long-term benefits, the system must be integrated with other systems as there already exist multiple different systems. It would be great if a new tool could eliminate several existing ones.	• The tool could be helpful, if process participants understand it in order to work with it. • The tool can provide a strong information value and a good basis for communication if it is used correctly. • To ensure long-term use of the tool a proper integration into existing systems is necessary. • The product innovation process can probably benefit greatly from such a tool. • Work should not be too data-based as interpretation is crucial. • Looking back into the past to recommend action can help, but every new instance is slightly different. • The user should be able to select the data basis themselves. • To broaden the database, data is needed that goes beyond the PLM. • The dashboard should not only display information, but should be integrated to the extent that data can also be entered. Preferably, it should not just be a file upload, but should also be able to be entered directly in the corresponding interface. • Appropriate training for process participants should be provided to introduce the system in order to avoid operating errors.

Table 4
Iteration 1: focus group feedback

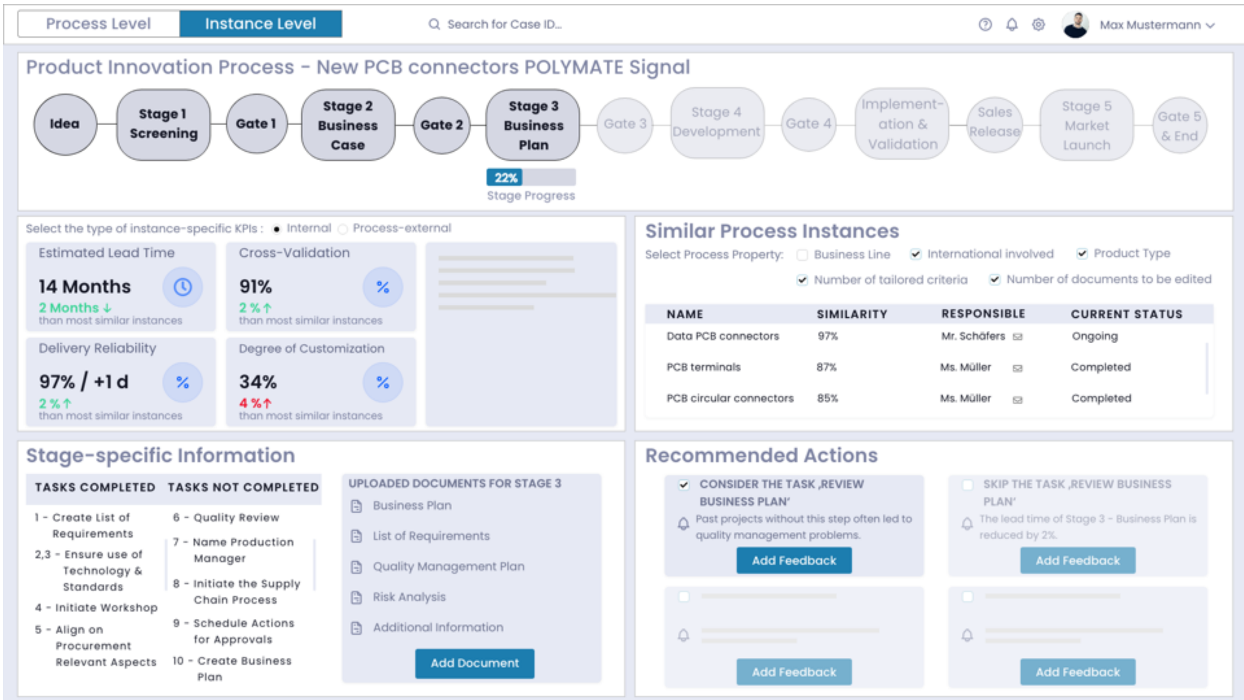


Figure 9: Refined GUI of the IT artifact - instance level stage perspective

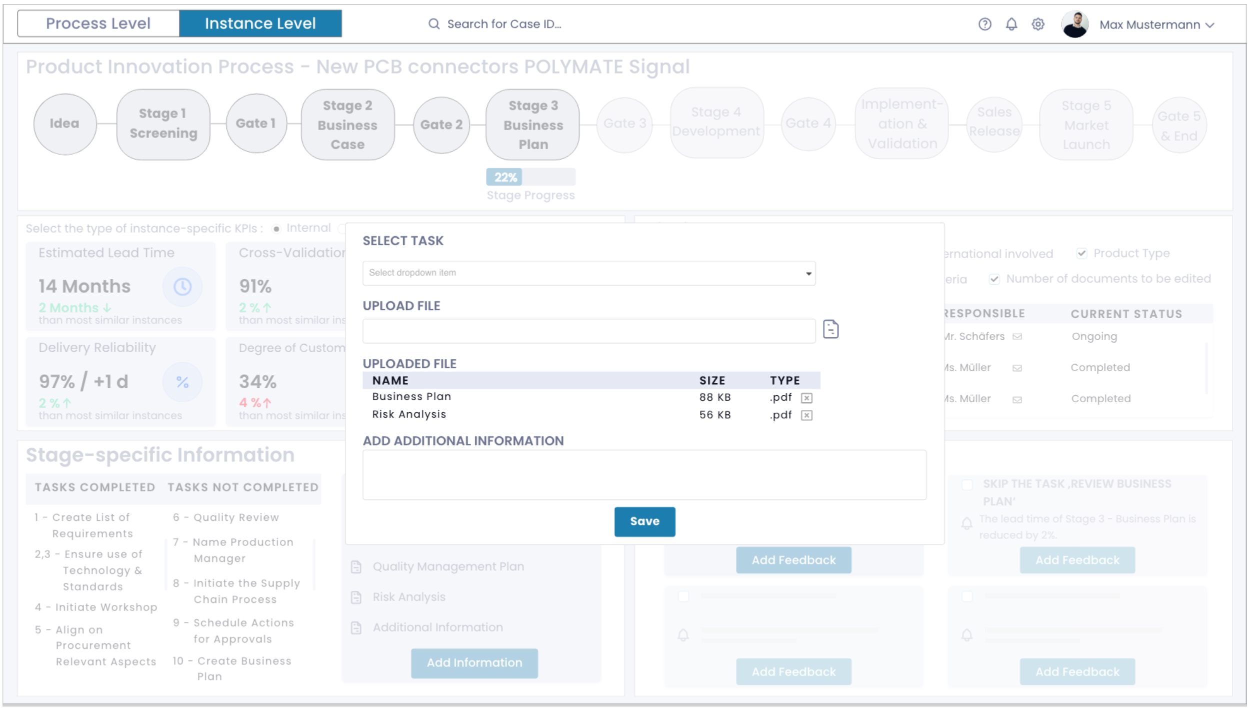


Figure 10: Refined GUI of the IT artifact - instance level stage perspective additional information

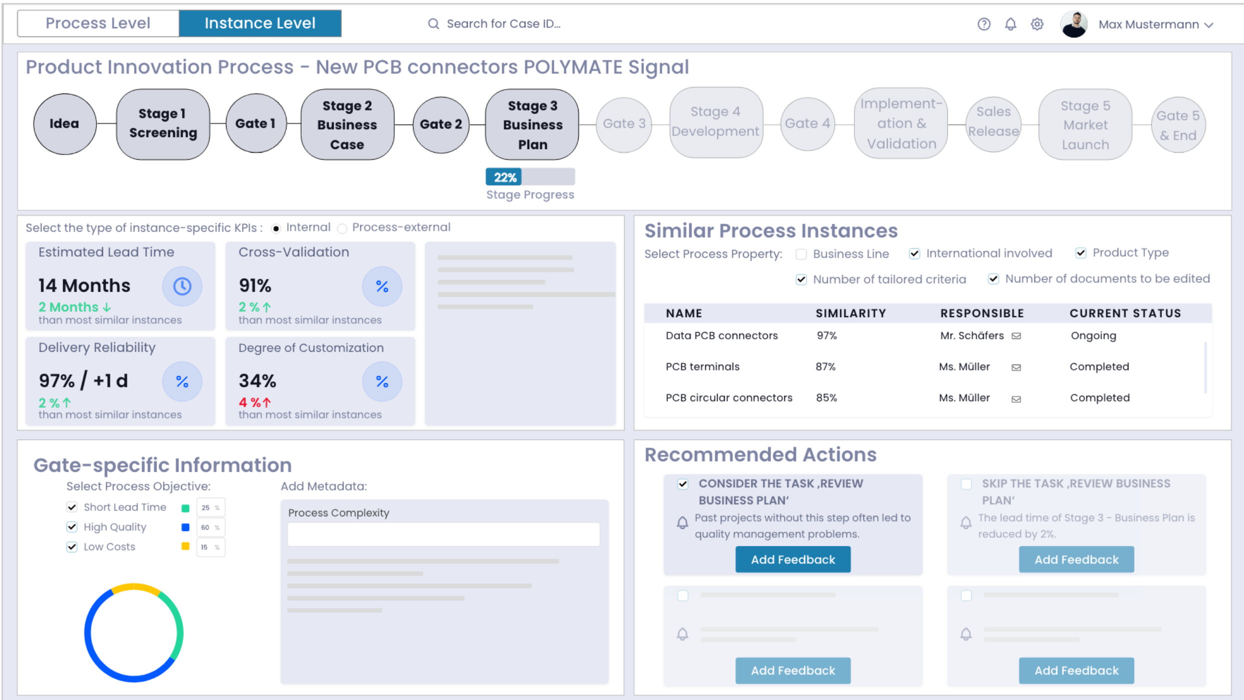


Figure 11: Refined GUI of the IT artifact - instance level gate perspective

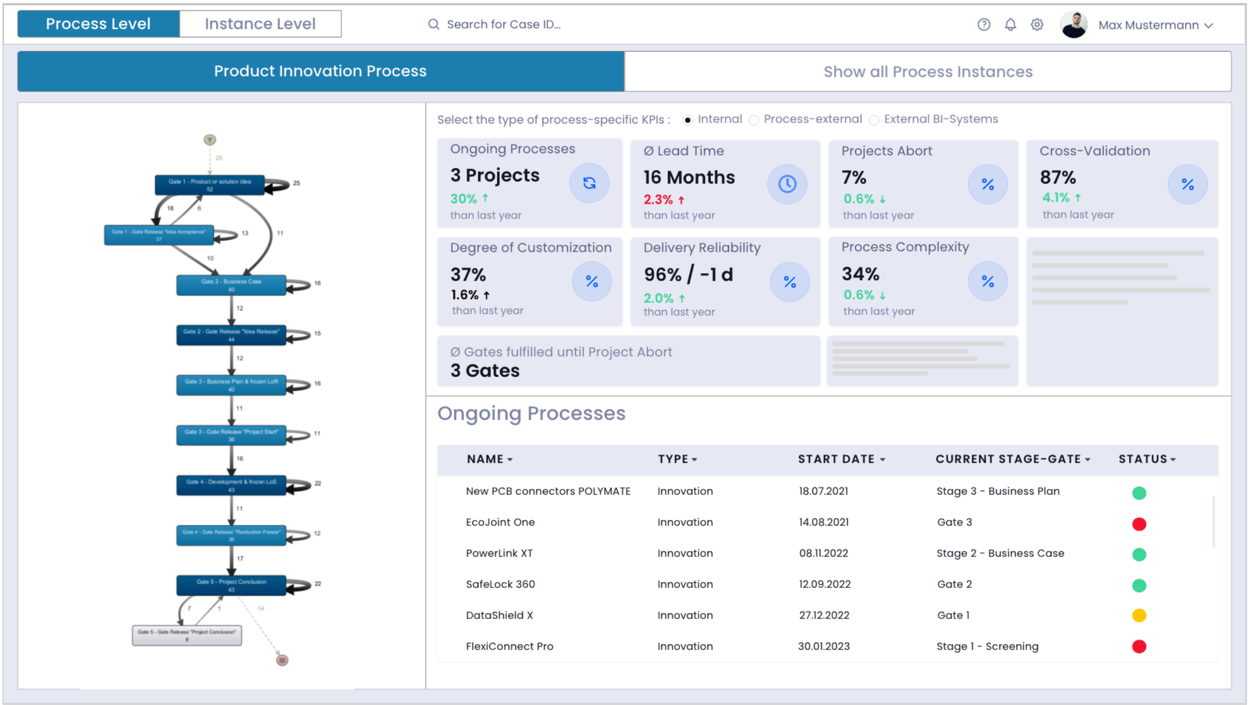


Figure 12: Refined GUI of the IT artifact - process level

Feedback Fluid Processing Ltd.	**Feedback Industrial Connectors Inc.**
• Similar instances still need to be enriched in order to obtain more concrete information from past instances. • SAP was often consulted for the individual instances. • Strengthen the general emphasis on recommendations for action. • Cluster descriptions for similar process instances were positively emphasized several times. The information in the descriptions could be used for communication with the management. However, it would be helpful to be able to select individual criteria for individual projects. • It was helpful to see the status of a process instance at a glance, but more information should be shown regarding individual activities. • Currently relevant or responsible persons for each activity should also be shown. • The system should offer the possibility to jump directly into other systems, as currently not all necessary information are available.	• The possibility to switch between process and instance level was positively received. • Visualization and status of a process instance were noted as particularly important. • It was helpful to see similar process instances, however, more information about a specific process instance is necessary. • It was difficult to derive useful knowledge as individual process activities are too different. This still requires too much detailed knowledge, which is not yet included in the tool. • Recommended action can add value. They can influence future process instances based on current or historical ones as insights can be drawn from them. • A feedback loop is important for the recommended actions so that it is possible to understand which action had which effects. • The descriptions for clusters regarding the similar process instances could be improved. • The roles of the process participants should be maintained so that it can be identified who has particular expertise.

Table 5
Iteration 2: simulation game feedback

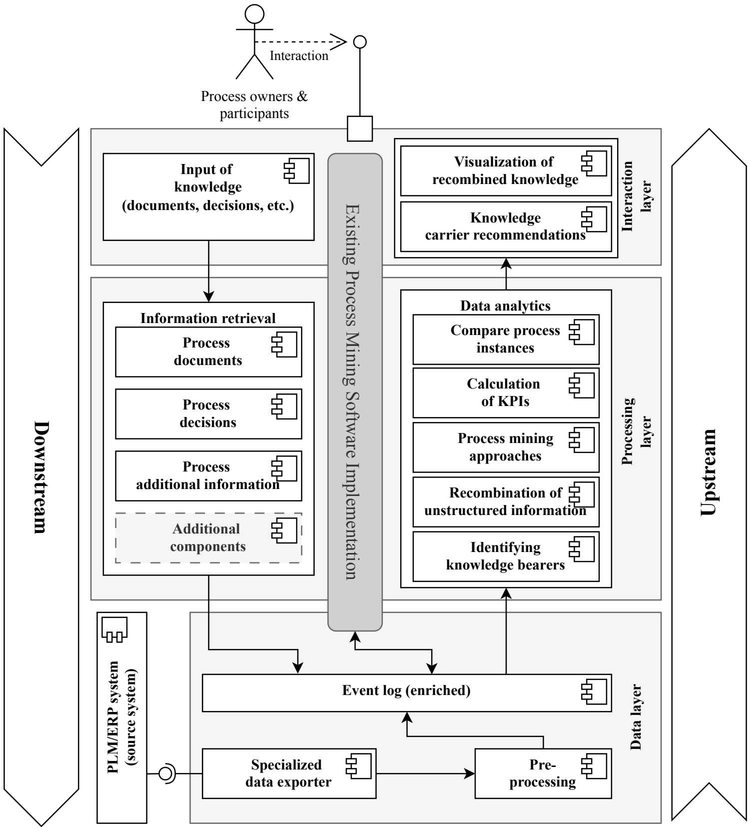


Figure 13: Layered architecture of the IT artifact

Proposition 1: Identification and differentiation of activities

- Difficult to draw a clear line between knowledge-intensive and administrative tasks.
- Additional documents are already being added at Fluid Processing Ltd.
- The differentiation will additionally help with the communication of the process to other relevant parties.

Proposition 2: Enhancement of the event log with external knowledge

- This has a positive long-term effect on the data quality.

Proposition 3: Retrievement and combination of knowledge from similar past process instances

- Very dependent on the data quality.
- Estimating other long-term effects remained difficult.
- Works councils are a general topic with regard to the ability to act.

Proposition 4: Identification and connection of knowledge bearers within the processes

- Networking is important, especially for new process participants.

Proposition 5: Derivation of actionable interventions with the possibility to provide reasoning on decisions to evaluate past decisions' effects on process goals

- It has to be clear whether these propositions and their actions address the instance of a process or the process in general.
- Important to learn from the decisions.

Table 6
Iteration 3: internal qualitative feedback - key statements

Criteria	Average	Median	Std. Deviation	Min	Max
P1A	4.65	5	0.70	2	5
P1I	4.74	5	0.53	3	5
P1NI	3.57	4	0.97	2	2
P1AG	3.65	4	1.17	1	5
P1E	4.09	4	0.97	2	5
P2A	4.43	5	0.82	2	5
P2I	4.78	5	0.51	3	5
P2NI	4.09	4	0.88	2	5
P2AG	3.48	4	0.83	2	5
P2E	4.30	4	0.69	3	5
P3A	4.52	5	0.77	3	5
P3I	4.57	5	0.88	2	5
P3NI	3.83	4	0.87	2	5
P3AG	3.74	4	1.07	1	5
P3E	4.43	4	0.58	3	5
P4A	4.74	5	0.44	4	5
P4I	4.52	5	0.77	3	5
P4NI	4.22	4	0.72	3	5
P4AG	3.87	4	1.15	1	5
P4E	4.22	4	1.02	1	5
P5A	4.57	5	0.58	3	5
P5I	4.43	5	0.88	2	5
P5NI	3.26	3	1.19	1	5
P5AG	3.39	4	0.92	2	5
P5E	4.35	5	0.91	2	5

P1 - P5 = Proposition 1 to 5
A = Accessibility
I = Importance
NI = Novelty and Insightfulness
AG = Actability and Guidance
E = Effectiveness

Table 7
Iteration 3: quantitative feedback

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