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Highlights

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- We report an ADR study developing a KIP-specific process mining artifact.
- We offer design principles supporting knowledge creation in KIPs through process mining.
- We show that a solid knowledge base and exchange culture help participants make strategic decisions in KIPs.
- We provide organizations insights to manage KIPs by converting tacit knowledge.

Supporting Organizational Knowledge Creation in Knowledge-Intensive Processes through Process Mining

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ABSTRACT

Knowledge-intensive processes (KIPs) are complex, strategic core processes that drive organizational competitive advantage. These processes rely on explicit and tacit knowledge. While explicit knowledge can be codified and leveraged—often through technologies such as process mining—tacit knowledge remains embedded in individual process participants, limiting knowledge transfer and organizational learning. Process mining, a data-driven approach to analyze process data, works best for standard processes that are managed for consistency, costs, and time but is insufficiently equipped to enhance KIPs, which depend on dynamic, experience-based decision-making. We present findings from a 39-month Action Design Research (ADR) project to conceptualize a new class of IT artifacts that enable process mining for KIPs. This class of IT artifacts integrates richer process-related information, facilitating knowledge transfer by allowing participants to learn from similar process instances and engage in socialization. We propose five theory-ingrained design principles that guide the development of such systems and examine their role in fostering knowledge creation within organizations. Our research bridges critical gaps between business process management and knowledge management, offering theoretical and managerial insights. For practitioners, our findings provide a foundation for improving knowledge-intensive processes, ultimately upgrading strategic decision-making and organizational performance.

1. Introduction

Knowledge-intensive processes (KIPs) [1], such as research & development or product innovation [2], represent a strategic aspect of modern organizations [3] because they enable leveraging specialized knowledge for organization's competitive advantage [4, 5, 6, 7, 8, 9]. KIPs rely heavily on individuals' tacit knowledge, their creativity, and their decision-making competence. Consequently, they are often less structured and more complex than operational business processes [1, 10, 2, 11].

Although KIPs are critical to organizational success [12], they are often manually managed by individual employees because existing technologies provide only limited functionality for addressing the complexity and unpredictability of such processes [1]. On the one hand, recent business process management (BPM) technologies, such as process mining, are primarily applicable to operational, standardized processes [13], while traditional process-aware information systems (e.g., ERP systems) offer limited capabilities for creating, sharing, and analyzing process-related knowledge in the form of unstructured data (e.g., documents, notes, images, drawings) [1, 10, 2, 11]. On the other hand, while knowledge management systems allow flexible communication and collaboration of individuals to generate and share knowledge [7, 8], they focus on individual tasks and lack an end-to-end process perspective [14, p.162].

Over the last years, process mining evolved as a promising approach to analyze and manage business processes in a data-driven way [15, 16]. At its core, process mining extracts event logs from information systems to discover as-is business processes, which are then analyzed by applying data mining and machine learning algorithms to assess and improve their performance [15, 16]. In a recent survey, decision makers of 800 companies viewed process mining as the most pertinent technology for improving business processes, with 61 % either using it already or intending to implement it within the next twelve months [17].

Most process mining approaches, however, are based on the assumption that all necessary information for analyzing business processes is available in the form of event logs, which contain metadata about the execution of activities within the process (e.g., which activity was executed? When? For how long? By whom?) [16, 15]. As a consequence,

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process mining works best for processes that exhibit a high degree of standardization and digitalization, such as order fulfillment or shipping processes [15, 18, 16]. However, this type of event logs cannot adequately represent KIPs in their full breadth and depth because event logs solely contain the explicit knowledge associated with a process (e.g., activities, control flow, and resources). Tacit knowledge (e.g., experience, skills, and intuition), in contrast, is typically not available in event logs [15] and, therefore, cannot be analyzed by process mining, even if this type of knowledge is crucial for strategic processes [19].

This paper addresses the identified gap between BPM and knowledge management by developing a new class of IT artifacts coined *process mining for knowledge-intensive processes*. We build on the theory of organizational knowledge creation as a kernel theory to inform the artifact design [20]. Primarily, our artifact enables the transformation of tacit knowledge into explicit knowledge to make it usable for process mining of KIPs [1, 21].

We conducted a 39-month Action Design Research (ADR) study [22] involving two case organizations and one technology provider, comprising three iterations of building, intervention, and evaluation. The ADR team comprised five researchers and five practitioners. We built and evaluated the IT artifact while applying it to two representative KIPs, i.e., a product innovation process and an engineer-to-order process. The three ADR iterations comprised 27 interviews, 72 workshops, seven focus groups, and three simulation games in the three involved organizations.

In line with the dual mission of design science research, our study solves an important business problem while contributing to theory. First, we iteratively built and evaluated an IT artifact for process mining for KIPs, which proved its usefulness in enabling organizations to manage process mining in KIPs and thus enable the strategic management of KIPs. Second, we abstracted and formalized the learnings from building and evaluating the artifact and condensed its insights into five theory-ingrained design principles [23], representing a type five theory for design and action [24].

Our results provide implications for theory and practice by converting tacit process-related knowledge into explicit knowledge. From a theoretical perspective, we enhance organizational knowledge creation by showing that our IT artifact can identify and network process participants to foster knowledge transfer through socialization. This integration of process participants' tacit process-related knowledge is not possible without the presented IT artifact. It enables the establishment of a well-grounded knowledge base and a culture of knowledge exchange, allowing process participants to make more objective strategic decisions in KIPs. From a managerial perspective, organizations can instantiate the five design principles to execute and manage KIPs based on mobilizing and converting tacit into explicit process-related knowledge that can be analyzed by means of process mining. Furthermore, we show that event logs can be extended beyond metadata with tacit process-related knowledge, which is usually manifested in unstructured data.

The remainder of this paper is structured as follows. In section two, we synthesize the fundamentals of process mining and knowledge management with a focus on KIPs. Section three outlines our ADR process, and section four describes its three iterations. In section five, we present the 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

Organizations continuously strive to improve and manage their business processes, as the quality of processes is key to an organization's operational performance [14]. Well-managed processes constitute a competitive advantage and secure an organization's position in the market [25]. BPM methods and tools support organizations in improving and managing their processes [14, 26]. Process mining, in particular, represents one state-of-the-art method to perform an in-depth analysis of processes based on data [15, 16]. It enables the design, implementation, control, and analysis of business processes involving people, organizations, documents, and other information sources [14, 26, 16]. Process mining helps organizations improve their processes by eliminating bottlenecks, enabling automation, or reducing process costs [16]. Due to its capability to process and analyze data in real-time [16, 27], live insights on the execution of a process can be gained, and ad hoc evidence-based decisions are possible [28]. In doing so, an organization can improve its dynamic capabilities to adjust itself to new exogenous influences [29], but also make sure that its processes are hard to imitate [30].

Existing process mining approaches are particularly applicable to highly digitalized and standardized processes as they work best with high volumes of accurate data [15, 16]. However, organizations also conduct processes that do not exhibit a high level of digitization and standardization, are less structured, and more complex [1, 10, 2, 11]. Such processes are termed knowledge-intensive processes (KIPs) [1] that are of strategic importance, such as product development and product innovation processes [2, 3, 31]. Due to their high level of complexity, their required flexibility [2, 10, 32], and the ambiguity surrounding their input and output [1], KIPs are difficult to predict [10, 21], digitize, and standardize [10]. Furthermore, human-centered and knowledge-intensive activities [1, 21], which play a pivotal role in KIPs and are essential for innovation [31], contribute to their variability, making task sequences subject to change based on individual actors' decisions and unforeseen events [1]. Thus, each process instance depends on the decisions and actions of single or multiple actors involved [1, 10, 2, 11, 33].

The high involvement of humans is the main source of complexity in KIPs [3], leading to difficulties in mapping them to a predefined process model [1] and resulting in multiple process variants [1, 2, 10, 11]. KIPs include unplanned and unscheduled knowledge development [1], on which each process instance strongly depends [1, 10, 2, 11]. Thereby, the intensity of the process-related knowledge is determined by the actions and decisions of process participants in situ [3].

So far, only a few approaches have been developed to support the application of process mining to KIPs. One such approach involves a framework that conceptualizes KIPs based on their distinct characteristics [34], which subsequently provided the foundation for a related tool [11]. Further studies used various data mining techniques to support the execution of KIPs, such as developing an approach to identify the flow of speech acts from event logs to demonstrate how this flow supports process performance analysis [35]. Another dynamic approach retrieves logs at runtime while incorporating domain knowledge specific to each process instance [36]. Clustering and classification techniques have been used to detect hidden patterns in KIPs, allowing the identification of KIP behavior and the generation of improvement recommendations [31]. Additional efforts include the mining and recommendation of templates for new KIPs using agenda-driven case management [37] and the development of a recommendation system that draws on similar, previously handled cases [38]. To manage KIPs in manufacturing, and particularly for product innovation processes, process mining has been utilized to identify and analyze maintenance operations in cellular manufacturing [39]. Additionally, process mining and case-based reasoning have been combined leveraging synthetic data [40]. Further advancements in predictive process mining combine machine learning and natural language processing to forecast the lead time of product innovation processes [41]. Beyond manufacturing, process mining has been applied in healthcare to examine a variety of patient treatment, diagnostic, and organizing tasks [42].

However, although first process mining approaches target KIPs, all available solutions only use a subset of the data relevant to KIPs [11, 10], negatively impacting the quality of process mining results [43]. The explicit knowledge [44, 20] associated with KIPs (e.g., its control flow, resources, etc.) is, in the best case, documented in the event log [18, 16]. In contrast, process participants' tacit knowledge [44, 20] is often hidden and depends on their willingness to document and communicate their insights [1]. So far, being unable to fully record tacit knowledge makes it difficult to determine its effect on a particular process instance, i.e., a single enactment of a process [1]. Thus, event logs lacking tacit knowledge are most likely unable to represent KIPs.

2.2. Organizational Knowledge Creation with Process Mining

Organizations increasingly rely on knowledge work to remain competitive [4, 5, 6, 7, 8, 9]. Hence, efficient and effective knowledge management is not only crucial for an organization's success [9, 4, 5, 6], but also for managing their strategic processes. This includes not only the creation of new knowledge but also the strategic management and diffusion of existing knowledge [45]. However, to create new knowledge, an organization must access an individual's knowledge and integrate it into the organization's knowledge system [46, 5] because organizations cannot create knowledge independently [5].

According to the theory of organizational knowledge creation, proposed by Nonaka and Takeuchi (1995) [20], mobilizing and converting tacit knowledge to explicit knowledge is the cornerstone of knowledge generation [20]. The SECI model (i.e., the four modes of socialization, externalization, combination, and internalization) describes that to expand knowledge beyond what an individual might know (referring to the ontological dimension), tacit knowledge must be converted into explicit knowledge (referring to the epistemological dimension) [5, 20]. Its four modes serve as the driving force behind the process of organizational knowledge creation and are interdependent [20, 47]. In a subsequent step, individual knowledge must be enhanced in an organization-wide effort through the modes of knowledge conversion, involving departments, divisions, and organizational boundaries, beginning with individuals and progressing to larger communities of interaction [20, 47].

Meanwhile, organizations must transform an ever-increasing amount of data that is generated in ever-shorter time intervals into organization-internal knowledge in order to remain competitive [48]. Hence, organizations employ digital technology to manage and analyze data and create knowledge [48, 9]. In knowledge management, technology and the social system are equally important and should interact with each other [46]. Knowledge management systems (KMS) [7] are used to support the management of tacit and explicit knowledge [4] (e.g., document management systems, collaboration and communication platforms, etc.), going beyond the conventional storing of codified knowledge and its retrieval [7]. While KMS may not appear to be different from other types of information systems, they aim to enable individuals to capture some of their knowledge in information or data as well as to assign meaning to the information and data the system provides [7]. It is important to use KMS to share a specific knowledge base so that individuals can achieve a similar understanding of data and information [7]. Consequently, KMS cannot be studied as separate entities or developed as stand-alone applications, but have to be integrated into other technologies that can be enhanced with knowledge management capabilities this way [4].

Managing knowledge is a dynamic and continuous challenge for organizations [7]. The SECI model provides a theoretical foundation for integrating process mining with knowledge management (see Figure 1). However, Figure 1 shows that current process mining approaches fail to sufficiently capture and use tacit process-related knowledge. Each process participant holds tacit knowledge about the execution of their local activities within a specific process instance, but this knowledge is rarely shared within the organization, limiting its dissemination [1]. Current process mining approaches focus on analyzing explicit knowledge, which is documented, for example, in the event log and in central documents (e.g., process models) [18, 16]. Yet, leveraging tacit knowledge is crucial to achieve overall process goals for KIPs as existing event logs incompletely and inaccurately represent KIPs [1]. Subsequently, abstracting data from specific instances and their context, deviations in a KIP cannot be interpreted on a process level anymore as order and time of activities are emphasized over context [18, 49, 50]. This leads to an ever-increasing spiral in which KIPs can only be analyzed, redesigned and executed on the basis of external available knowledge. Therefore, an organization must foster a culture of knowledge exchange, integration, and transformation among their process participants [20], because an individual's tacit knowledge that is not shared within the process will not contribute to the process-specific knowledge base [51]. Organizations should manage their process-related tacit knowledge wisely because it can open up a plethora of possibilities that constitute the innovativeness and creativity of an organization [52]. Therefore, organizations must understand how managing knowledge impacts organizational structures and their governance [53].

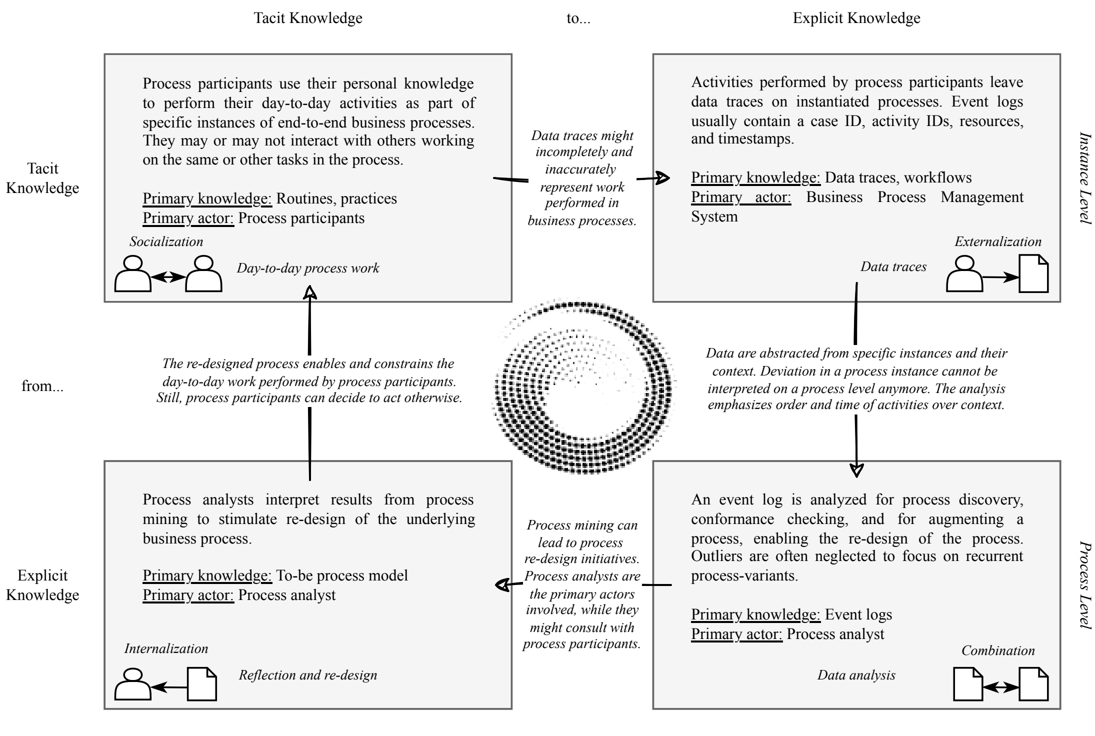

Figure 1: Organizational Knowledge Creation with Current Process Mining Approaches

3. Research Method

As a research paradigm, Design Science Research (DSR) addresses important organizational problems by developing innovative IT artifacts [54] while abstracting generalized theoretical knowledge, contributing type five theories for "design and action" to the knowledge base [24, 55]. One particular research method in DSR focusing on interventions in context is Action Design Research (ADR) [22]. According to Sein et al. [22], ADR comprises four phases: (1) problem formulation, (2) building, intervention, and evaluation, (3) reflection and learning, and (4) formalization of learning. Each phase follows specific principles, acknowledging close collaboration between scientists and practitioners. The first three phases are reiterated until the "formalization of learning" phase concludes the ADR process. One way to formalize the results is by developing design principles [23], which prescribe how a class of IT artifacts ought to be designed and how it can be instantiated in a similar context. The reusability of design principles is a critical characteristic that can be evaluated by five criteria, including (1) accessibility, (2) importance, (3) novelty and insightfulness, (4) actability and guidance, and (5) effectiveness [56].

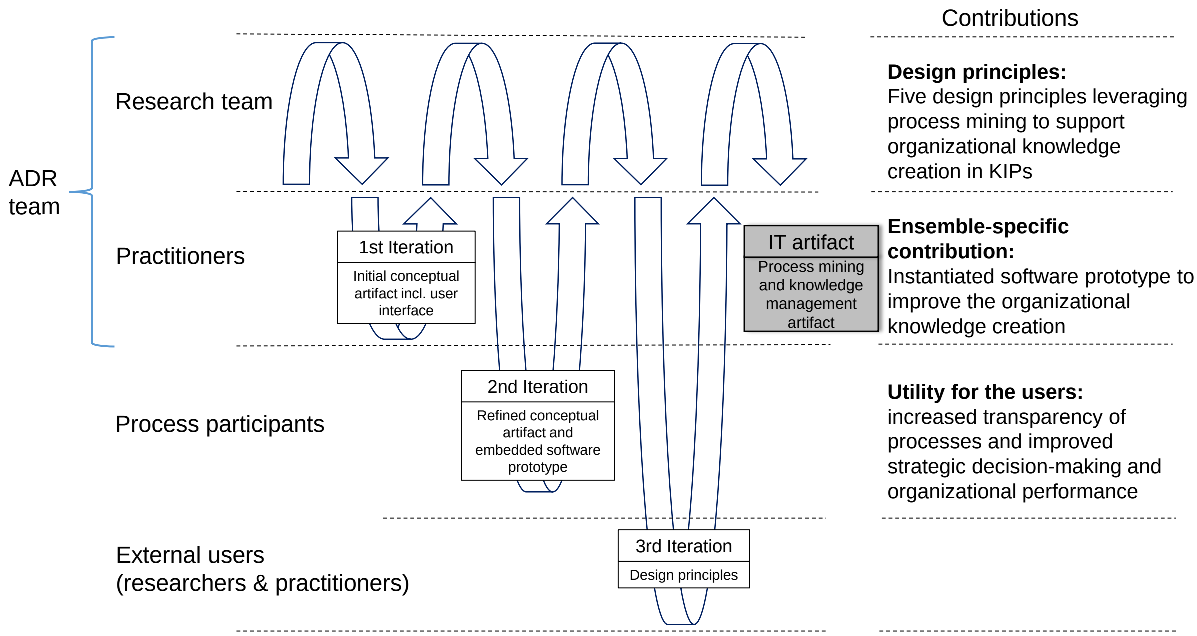

Figure 2: Action Design Research Process

In our ADR project, we conducted three iterations, each comprising a "building, intervention, and evaluation (BIE)" phase followed by a "reflection and learning" phase (see 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, with one mass-producing industrial connectors (*Industrial Connectors Inc.*) and the other producing 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 enabled the creation and embedding of the software prototype. Further details about the involved case organizations are summarized in Table 1. The close cooperation with the practitioners, as envisioned by ADR [22], enabled us to gain detailed insights into the focal KIPs.

	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 1
Overview of Case Organizations and Processes

4. Process Mining for Organizational Knowledge Creation in KIPs

4.1. Problem Statement

Starting with our ADR journey, we initially defined and detailed the underlying business problem. In doing so, we conducted an in-depth analysis of the existing literature on KIPs and BPM including process mining. To support the literature insights from a practice-oriented perspective, we additionally used the expertise of the organizations involved in the ADR project. We conducted workshops to gather domain knowledge and identify relevant KIPs. To better understand the context, we additionally conducted 27 semi-structured interviews (40 hours in total) with process participants (e.g., operational workers, higher management roles, etc.) from both organizations. We additionally analyzed the process-related information systems (i.e., the product lifecycle management system, the workflow management system, and the ERP system) and their underlying data structures to identify the amount and quality of data available and evaluated their maturity level for process mining [15]. In total, we conducted 49 workshops, comprising more than 125 hours of direct interactions with the case organizations. We identified that the investigated KIPs have multiple control flows that depend on the starting conditions of each process instance. Moreover, data integrity issues became apparent, making the ad hoc usage of traditional data analysis and knowledge management approaches challenging. Hence, tacit knowledge that has been transformed into explicit knowledge and was used for strategic decision-making in the KIPs was rare to find. This knowledge was bound to individual key users of the involved information systems.

Integrating the insights obtained from the literature (see section 2 and for the case organizations see Appendix Table 7), we identified three preliminary solution properties of a potential IT artifact: (SP1) to deal with the high variability of processes and corresponding data due to the diverse control flows and general complexity of KIPs, (SP2) to allow for adding and codifying implicit knowledge in relation to the corresponding process instances as this knowledge is otherwise dependent on the individual person, and (SP3) to enable a systematic storing and distribution of process-related knowledge.

4.2. First ADR Iteration: Conceptual Development

4.2.1. Building, Intervention, and Evaluation

In the first iteration, we built a conceptual IT artifact with an initial graphical user interface of a tool that incorporates knowledge management capabilities and process mining techniques based on the described solution properties. 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 [22].

The developed user interface features two views, distinguishing a process level from 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 domain-specific 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), context-dependent PPIs are shown. By considering the selected process properties and the defined goals, process instances similar to the analyzed case are identified, displayed, and clustered.

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 3). In general, the conceptual IT artifact was assessed positively. The participants stated that it provided 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 information but also to enable the possibility to add new information. However, guidance was needed on how to enter new information 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.

> *"However, the most important aspect is that the current data basis is improved. What is currently visible in our system does not correspond with reality. The added value only becomes visible when the data basis is enhanced and correct."* (IT Manager of Fluid Processing Ltd.)

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. This is crucial to ensure the long-term commitment of process participants. We further learned that it is important to identify and store historic strategic decisions made in KIPs and to provide a function for adding a post-assessment of the consequences of a specific decision (i.e., a feedback loop). We additionally learned that measuring the similarity of two process instances is 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 goals articulated by the customer have an overwriting relevance and must be taken into consideration to identify similar cases. Finally, the practitioners asked to provide detailed information on the actions taken and their effectiveness in the tool.

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 extended the conceptual IT artifact (see Figure 3) by incorporating functionality for adding new process-related information, to adjust the similarity of process instances dependent on the particular situation and goals, and for recommending actions with an integrated feedback loop. To incorporate all relevant components, we had several coordination meetings with the project partners.

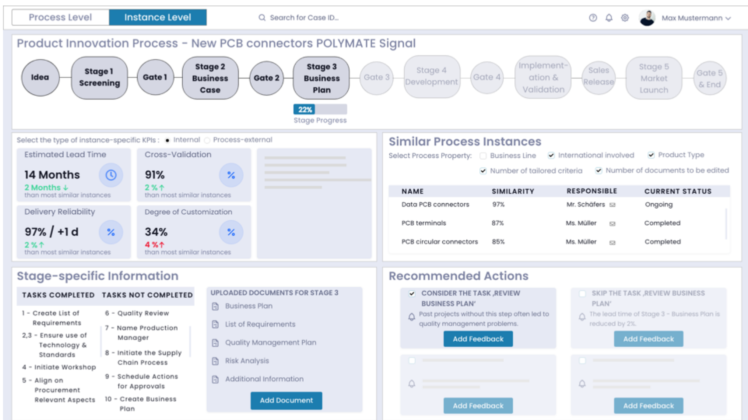

Figure 3: Refined GUI of the IT Artifact

In the second iteration, we transformed the refined conceptual IT artifact into a working prototype. Therefore, 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 software consists of three layers (see Figure 4). The data layer is responsible for extracting data from the source systems and preprocessing it to enrich the event log. Therefore, we developed specific data interfaces to build a connection between the process instances displayed in the prototype and other information systems used (i.e., the PLM and ERP systems). The processing layer is responsible for analyzing the event log by means of process mining and other machine-learning approaches. Furthermore, it processes input from the users, which has to be reintegrated into the event log. The graphical layer (i.e., user interface adapted from the conceptual IT artifact) is responsible for visualizing process-related information and recommendations, while also taking the user input such as decisions and documents.

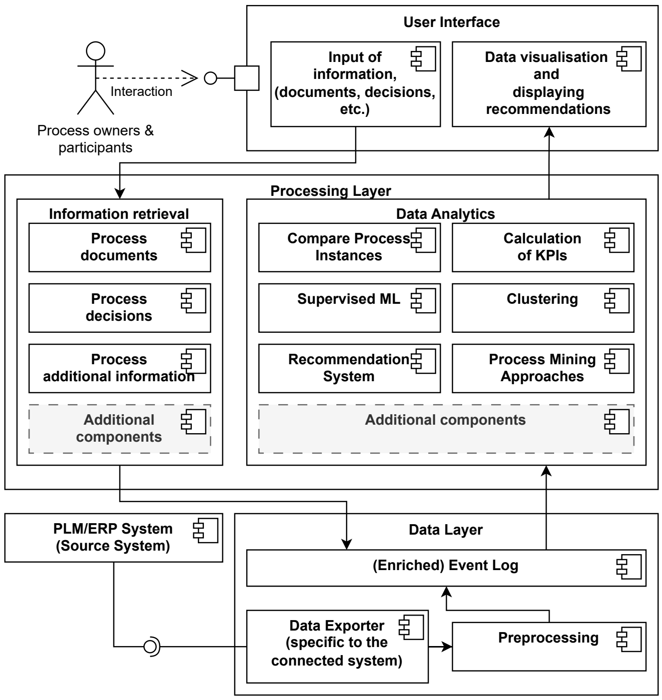

Figure 4: Layered Architecture of the IT Artifact

To validate whether the prototype supports process participants in their decision-making and execution of KIPs by making tacit knowledge better accessible, we conducted an intervention, comprising 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 24h of direct interaction. During the first workshop, we clarified the underlying business problem and communicated the implemented design decisions and features of the IT artifact to prepare the participants for the simulation game. Subsequently, the simulation game was carried out. For the simulation game, we simulated the respective KIPs due to their long lead times by observing process instances at specific moments, completing tasks, and fast-forward time (e.g., by three weeks) to simulate progress (see Figure 5). For each organization, four concrete evaluation scenarios were defined for the management of KIPs based on real historical events.

After the simulation game, we directly conducted a feedback session and distributed a survey to the participants to evaluate the prototype holistically (see Appendix Table 4). The prototype's functions were classified as important and useful by both organizations, especially the possibility to view similar process instances. However, although the participants from *Fluid Processing Ltd.* found that the presented information in the prototype is helpful, especially for

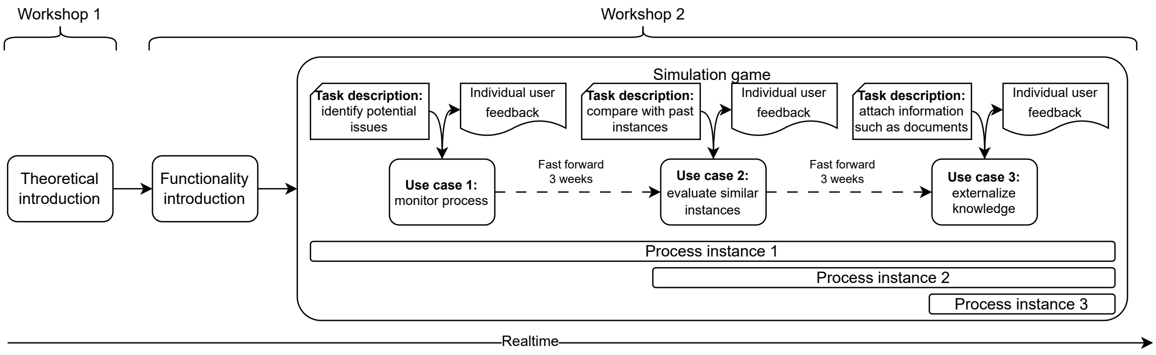

Figure 5: Visualization of the Simulation Game

communicating strategic decisions to the management, they stated that not all required information was available yet, for example, regarding individual activities. *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. Additionally, we received feedback that indicating other relevant process participants would be helpful to support knowledge exchange.

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 four major learnings. First, focusing on individual activities and distinguishing knowledge-intensive from administrative activities is crucial to present activity-specific information. Second, a well-integrated system must be established to ensure its usability and the availability of information. Third, relevant other process participants should be identified. Fourth, 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.

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 [56]. The five propositions (see Appendix Table 9) comprise (1) the identification and differentiation of activities, (2) the enhancement of the event log with external knowledge, (3) the retrieval and combination of knowledge from similar past process instances, (4) the identification and networking of knowledge carriers within the processes, and (5) the derivation of actionable interventions with the possibility to provide reasoning on decisions to evaluate past decisions' effects on process goals.

To evaluate the propositions, we conducted an internal and an external evaluation for reusability [56]. 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 5). 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. (2020) [23]). The participants were then asked to give quantitative (see Appendix Table 6 and Figure 8) 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

[1] Iteration 3: Qualitative External Feedback

Table 6 and Figure 8), with the factors accessibility and effectiveness reaching high scores, while the factors actability and guidance received mixed reviews, especially for Proposition 1 and 3.

While the participants understood the basic idea behind the Propositon 1, they opposed the assumption that drawing a clear line between knowledge-intensive and administrative activities is difficult. Some noted that the relevant process has to be identified in the first place, which is a challenge in itself already. Moreover, several researchers and practitioners highlighted that differentiating between activities can already provide insights into the structure of the process as well as foster reflection on them.

Proposition 2 was highlighted as very important and helpful for any kind of process analysis. However, this proposition was identified as a significant challenge due to the complexities involved in transforming tacit into explicit knowledge. This is associated with corresponding conversion losses as well as the conversion of supplementary information into data in the event log. Another relevant challenge is the willingness of the process participants to share their knowledge since 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 and explained how they already asked other process participants to attach relevant documents to their ERP system.

Proposition 3 was perceived as mandatory. 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, and therefore, applying traditional process mining techniques will probably be difficult.

Most evaluation participants agreed with Proposition 4 and highlighted its novelty, while they also mentioned possible trust issues and the impact of the organizational culture on process participants' willingness to share 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" as finding a proper action is already difficult enough, 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 [23]. 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 and should be seen as a fundamental assumption. Regarding Proposition 2, we learned that it is a critical step for effective process analysis. However, the concept of converting tacit knowledge into explicit knowledge needs to be strengthened. Additionally, potential resistance was voiced by participants fearing their substitution. It is important to ensure the accuracy and reliability of added information to avoid conversion loss. From the feedback regarding Proposition 3, we learned that focusing on similar past process instances remains important. However, we concluded that a lack of data availability might hinder the application of current process mining methods, which emphasizes the importance of Proposition 2, aiming to access additional process-related data. Proposition 4 seems particularly valuable in large organizations where process participants may not know each other. However, we observed some 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. The feedback Proposition 5 showed that there is a need for clear definitions and upfront goal-setting to avoid ambiguity and guide actionable recommendations effectively to mitigate the risk of incorrect prescriptions. Additionally, fostering process participants' understanding and engagement through process mining insights is crucial for the successful implementation of and positive impact on strategic decisions. However, to actually take action, process participants are required to internalize the information gathered through process mining.

5. Formalization of Results

Based on what we learned over the three iterations (see Appendix Table 7, Table 8, and Table 9), we condensed the prescriptive knowledge gained into five design principles. The theory-ingrained principles draw upon the literature on knowledge management, especially the theory of organizational knowledge creation [20], and process mining [15, 16], as well as the insights gained from our research project. The developed design principles are mutually interdependent [20] and represent the flow of transforming tacit knowledge into information and data and vice versa (see Appendix Figure 9). Subsequently, we will briefly describe each design principle. A detailed overview in line with Gregor et al. (2020) [23] can be found in the Appendix in Table 10.

5.1. DP1: 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 carriers 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 information that can be shared allows others to build on this information and create new knowledge [47]. Knowledge is transformed into information after it has been expressed and displayed using words, images, text, etc. [7]. In our study, we observed that even though many organizations are aware of that fact and the problems it might cause, no sufficient mechanism is in place to convert tacit process-related knowledge to explicit information.

Because knowledge needs to be converted into information that can be accessed by others—including humans and information systems—the creation of organizational knowledge for KIPs needs to enable process participants to add their knowledge as unstructured information to the artifact. This includes writing down knowledge as text or creating a drawing, as well as adding other documents that might exist but have not been made available to co-workers or the organization yet. Thereby, a mechanism is needed that filters the "right" knowledge and relates it to the specific process instances so that we can understand which knowledge belongs to which process and in particular to which instance in order to use it for process mining.

5.2. DP2: Enhance Event Log with Categorized Information

While unstructured data often carry a high implicit value in itself, 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 [57]. Most algorithms for analyzing unstructured data build associations and search for correlations in the data. 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.

Hence, to support the creation of knowledge in KIPs through the use of process mining, we need to convert information into data and store it in the event log related to the specific process instance. Storing information as structured data in an event log implies categorizing and classifying the information first and assigning them as data to the event log represented as a new attribute. This means that not only information must be transformed into single data entries, but these data must also be categorized, and the categories must be named in a machine-readable and human-interpretable way. Thus, this extends the event log beyond its typical attributes.

5.3. DP3: 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 (1973) [58] 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 knowledge available as information [20, 47] is essential. 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 (i.e., 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 done by clustering (as stated by P6, R7, and R12). Hence, information about similar past process 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 (i.e., explain) about the reasons why the presented past process instances are viewed as similar. In doing so, existing process mining methods need to be extended through new techniques not only able to process structured data but also unstructured data in textual or even visual representations (e.g., natural language processing, computer vision, etc.). Thereby, it is important to especially consider predictive and action-oriented process mining techniques [16], as information generated through these techniques can support process participants in making decisions and in executing 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 integrate a feedback loop so that the system can learn further.

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

The knowledge creation process describes that knowledge is created by internalization of information, among other things [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, 47], closely related to *learning by doing* [47]. 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, we need 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 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: Identify and Network Knowledge Carriers through Process Mining

Individual knowledge cannot contribute much to the organizational knowledge base if it is not shared among individuals [51]. Through socialization, employees learn from each other, and share their experiences and individual knowledge, enriching their tacit knowledge base [20, 47]. However, concerning the availability and distribution of knowledge, employees who are knowledge carriers often remain hidden and cannot be easily identified. Thus, making it difficult to share their individual knowledge and learn from each other. In our study, we observed that for most problems that occurred or difficult questions that needed to be answered, 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 in KIPs, knowledge carriers 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 carriers 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 "reverse engineered", and thus, knowledge can be traced back to the process participant who initially entered the information on a similar process instance in the past.

6. Discussion

Our study makes important contributions towards advancing process mining into a method that can be used for managing KIPs that rely heavily on tacit knowledge that is not usually captured in even logs. Also, our approach promotes innovative ways of fostering organizational knowledge creation with process mining. The implementation of the developed design principles affects both the epistemological and ontological dimensions rooted in the theory of organizational knowledge creation [20]. Table 2 summarizes how our approach differs from the use of current process mining approaches.

6.1. Process Mining for KIPs from an Epistemological Perspective

The epistemological dimension rooted in the theory of organizational knowledge creation is concerned with the transformation of tacit into explicit knowledge. This transformation is driven by the four mechanisms of socialization, externalization, combination, and internalization [20]. The design principles we developed directly support these transformation steps of converting tacit into explicit knowledge in KIPs as they follow the SECI model and thus enable applying process mining to support knowledge creation in KIPs (see figure 6).

The first design principle on externalizing tacit process-related knowledge to information is based on the externalization mode [20, 47], which covers the process of transforming tacit knowledge into explicit knowledge

Concept	Current process mining approaches	Process mining for 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	Internal quality criteria, e.g., control flow, bottlenecks, resource consumption, cost, time	External quality criteria, e.g., customer satisfaction, value co-creation, adaptability, exception handling, solution-orientation
Primary unit of analysis	Process on a type level	Process instances
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 knowledge-intensive processes

Table 2
Current vs. KIP-specific Process Mining Approaches for Knowledge Creation

[20]. However, current IT artifacts primarily handle codified, explicit organizational knowledge [7]. This also applies to process mining, which focuses on the data available in event logs [16, 18]. However, integrating knowledge management capabilities into process mining provides the potential to broaden IT-based knowledge provision to include other forms and types of knowledge, such as process participants' tacit knowledge [7].

Based on the mode of combination, design principles two and three evolved that deal with enhancing the event log with classified information (see DP2) as well as the retrieval of information from the event log (see DP3). It is commonly overlooked to include unstructured domain data in event logs, although they would have the potential to provide useful insights and improve contextualization [57]. Therefore, it is even more important to enrich the event log with data that is not commonly included in the event log. Common event logs include the case ID, activities, and timestamps, making process mining best applicable to processes in which directly follows relationships and time are the most crucial factors. In KIPs, however, external factors like customer satisfaction are more important than reducing times of business processes. This may have implications for the eXtensible Event Stream (XES) standard, which deals with standardizing a language for exchanging, storing, and transporting process event data [59]. Further implications relate to the maturity levels of the event log that range from excellent to poor quality [15]. Considering that diverse processes have different requirements, this affects the currently existing approaches and calls for a refinement of the XES standard and the event log maturity levels.

Additionally, existing process mining methods need to be extended through new techniques 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 Large Language Models (LLMs) to handle textual data [41, 60, 61, 62]. Thus, including knowledge creation capabilities into existing technologies [4], such as process mining, is essential, because social actors take a while to transform data into information [46]. With this kind of technology, it is possible to analyze the gathered data [4]. This supports 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 execution 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. Additionally, the concept of adaptive case management (already used in the healthcare domain) can be used, which intends to gather knowledge and information from the KIPs and aims to store information that may be crucial for handling a similar process instance in the future [37, 63].

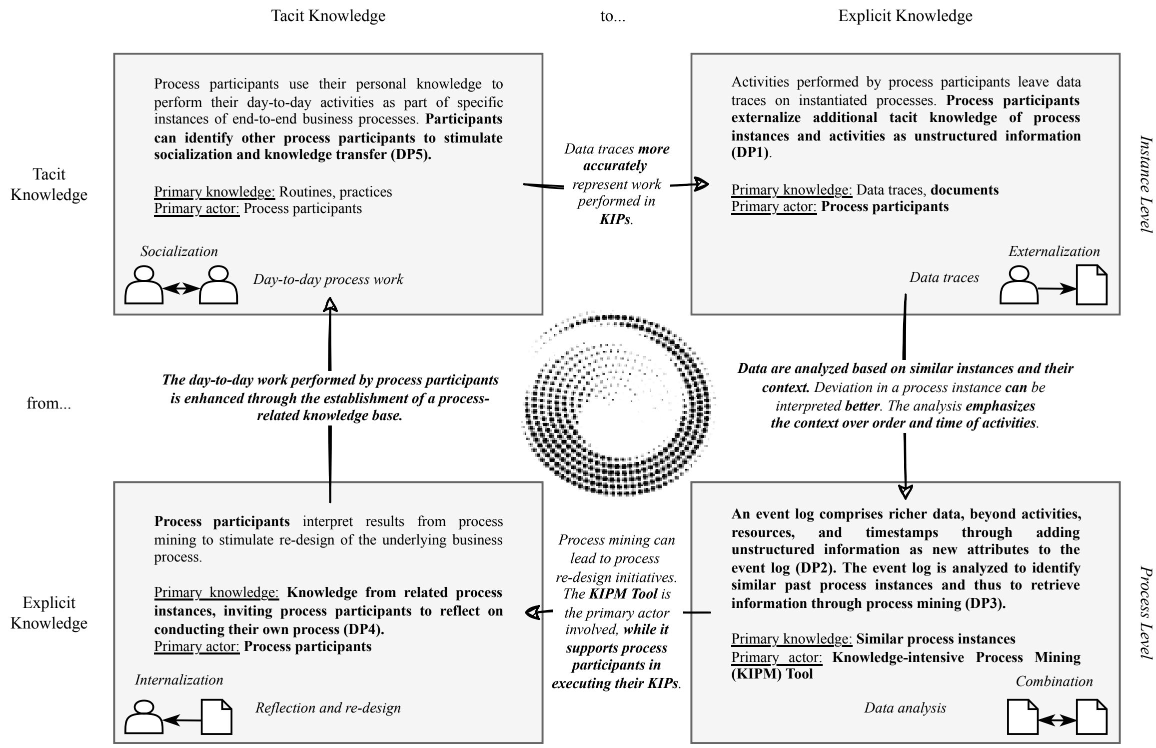

Figure 6: Organizational Knowledge Creation with Process Mining for KIPs

The best way to transform information into knowledge is through social actors [46]. Therefore, our approach foregrounds participants as users of process mining, whereas traditional process mining focuses on process analysts as users. 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, 47]. Whereas information technology is effective in handling the conversion between data and information, it is not a good replacement for turning information into knowledge. Information technology can only support process participants in internalizing new knowledge [46]. Traditional process mining rather informs process analysts so that they can re-design processes that are then executed by process participants. Our approach, however, aims to present process participants with relevant information related to their specific process instance. This 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 in a process mining tool so that process participants can directly ask for information regarding their process instance or specific activity. As LLMs can process the structure of event logs and textual information, they are able to capture all relevant information regarding KIPs.

The last design principle aims at networking different knowledge carriers and is driven by the mode of socialization [20, 47]. Through this, knowledge carriers can be identified and connected to interact with each other. This is particularly important because new knowledge in organizations arises from productive dialogue [64]. Furthermore, the expansion of an individual's network to encompass more extended connections, though potentially weaker, is a pivotal aspect of the knowledge diffusion process [65]. Such networks facilitate exposure to a greater diversity of ideas, enhancing the potential for knowledge acquisition and innovation [65]. Thus, the access to and dissemination of information and knowledge among process participants can bring new perspectives [51]. 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]. The search for knowledge sources is often constrained to immediate colleagues with whom the individual has regular and routine contact [7]. Nevertheless, to build knowledge networks, the concept of organizational mining can be adopted and integrated into process mining, which takes on the resource perspective of a process [16]. The goal of organizational mining is to discover and analyze social networks, revealing how resources have collaborated to execute individual process instances [16]. Collaborations of different resources can be visualized as graph social networks, in which the nodes represent the resources and the arcs represent the form of collaboration between pairs of resources [66]. In an event log of a KIP, the information about the resource performing an activity in the process is documented. Thus, we can analyze the social network behind each process instance and create a knowledge network surrounding the KIP. This further enables us to reverse engineer the knowledge transformation process, so that we can identify specific knowledge carriers for different topics related to the KIP.

6.2. Process Mining for KIPs from an Ontological Perspective

Because organizations cannot create knowledge on an abstract level, individually created knowledge is amplified and crystallized as part of an organization's knowledge network [20]. Thus, before knowledge can be utilized at the organizational level, it must be distributed and shared throughout the organization [46]. The way that people, organizational technologies, and techniques interact can directly affect if and how knowledge is distributed [46]. Therefore, supporting the ontological dimension enables the transformation of individual knowledge into group or organizational knowledge [20]. Nevertheless, identifying knowledge, making it accessible to other employees, and combining it remain major challenges to creating new organizational knowledge [67].

In the context of KIPs, it is important to go beyond approaches that manage processes and process-related knowledge separately [21, 48]. Therefore, organizations need to integrate BPM with knowledge management capabilities [68]. Adapting the theory of organizational knowledge creation to the field of BPM enables us to exchange and share knowledge among process participants and make knowledge about KIPs available to others, as discussed in detail in section 6.1 and Figure 6. Our IT artifact supports a process of knowledge creation in KIPs that differs strongly from the knowledge creation that is fostered by current process mining approaches (cf. section 2.2). Thus, we not only enable organizations to make tacit knowledge related to a KIP explicit but also enable new ways of creating organizational knowledge with our innovative process mining approach. Through implementing our design principles, process-related knowledge on an individual level and knowledge related to specific instances of a KIP will be crystallized at a higher ontological dimension (see 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.

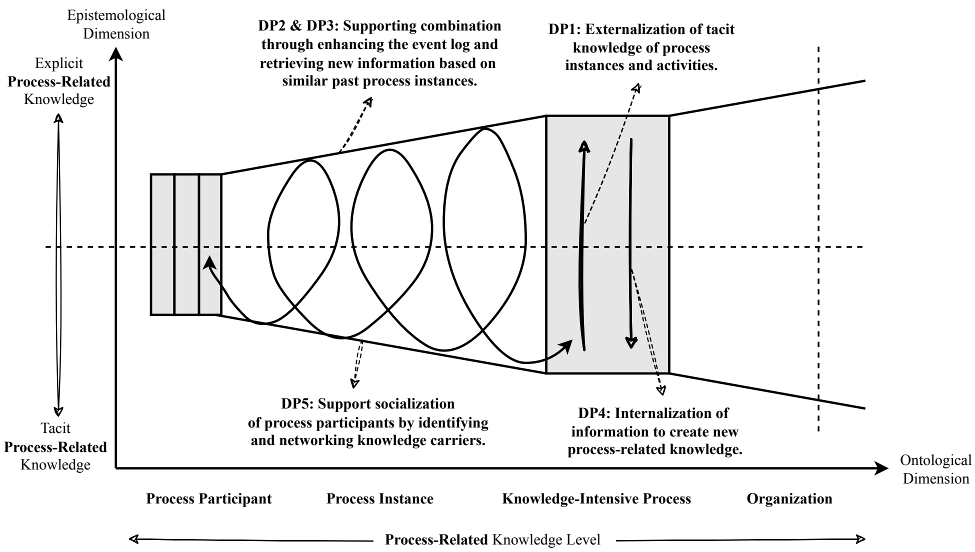

Figure 7: Supporting the Ontological Dimension with Process Mining of KIPs

As a result, a well-grounded knowledge base can be established, which can then be used to adapt and improve the KIP, based on a growing amount of data and available information [48]. This is important because managing knowledge serves as the foundation for effective process management, adjustment, and implementation [48]. Nevertheless, to capitalize on knowledge, an organization must balance its knowledge management activities subject to changes in organizational culture, technologies, and techniques [46]. 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 are essential components 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 [46]. Focusing on process mining as a technology helps align an organization's process and knowledge management activities [68] and capitalizing on the growing amount of process-related data [16]. Vice versa, if the increasing database is not effectively analyzed and managed, the complexity of the business process is increasing, which might have adverse consequences for an organization.

7. Conclusion, Limitations, and Outlook

In this paper, we prescribe how process mining can be used to support organizational knowledge creation in KIPs. We conducted an ADR project with two case organizations and one technology provider and developed five theory-ingrained design principles. Our design principles propose to (1) externalize knowledge to information, (2) enhance the event log with classified information, (3) retrieve new information from the KIP-specific event log, (4) internalize knowledge, and (5) network knowledge carriers. We contribute to the existing research streams on knowledge management and process mining. In contrast to traditional process mining, which makes more generalized statements in order to support a general management or redesign of the process, our approach enables the mobilization and conversion of an individual's tacit knowledge about a KIP as well as the conversion of this knowledge to a higher ontological level. In doing so, a process-related knowledge base can be established so that process participants can make better informed strategic decisions in KIPs.

We acknowledge that the generalizability of our results is limited to the experiences of the involved case organizations in our ADR study, which may present a narrow view. Even though we conducted an internal and external evaluation to ensure the validity and reusability of the design principles, applying the developed design principles in future research to other organizations might result in their further refinement.

A. Appendix

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 3
Iteration 1: Focus Group Feedback

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 4
Iteration 2: Simulation Game Feedback

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 carriers 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 5
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 6
Iteration 3: Quantitative Feedback

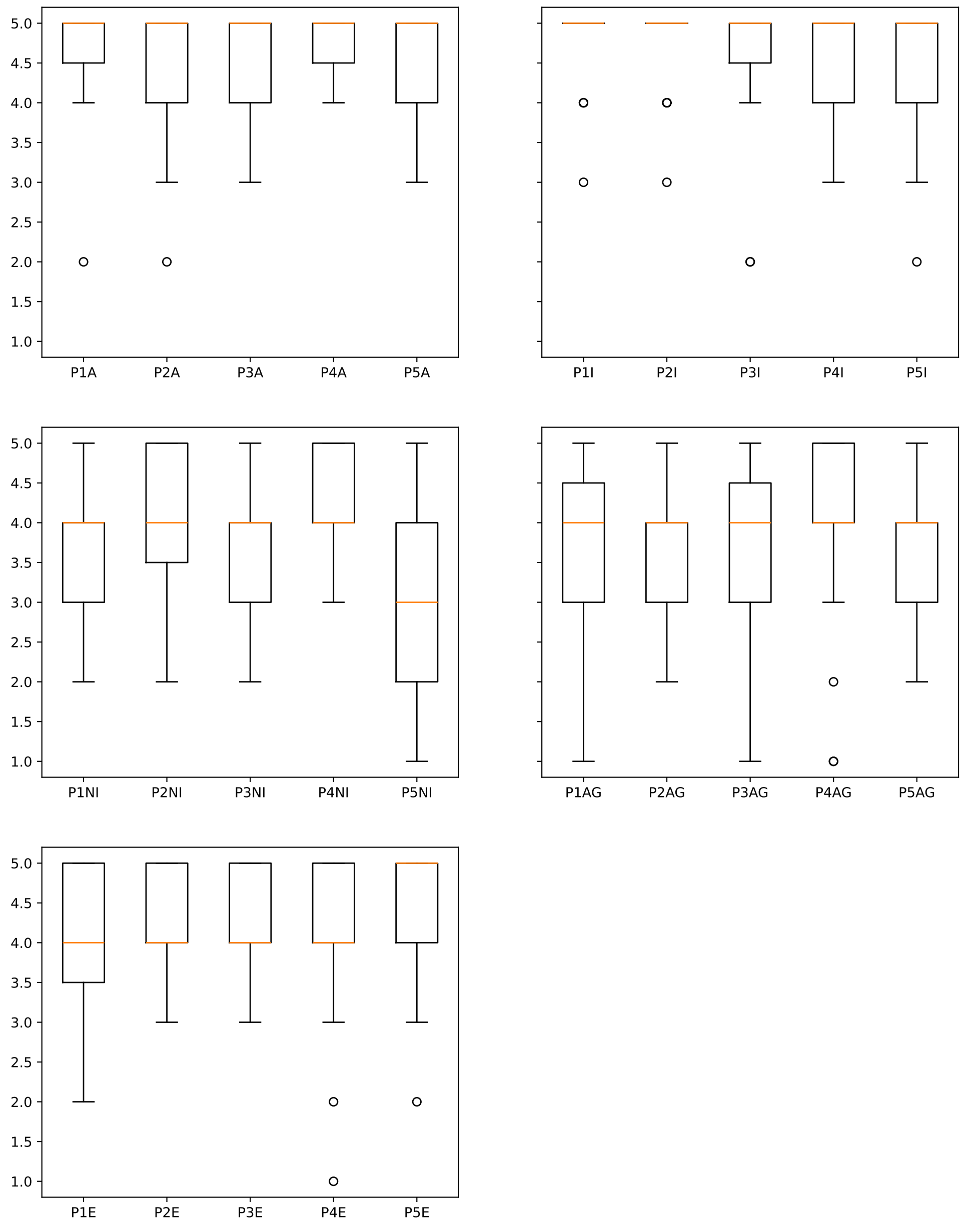

Figure 8: Iteration 3: Quantitative Feedback

Preliminary Work		
27 semi-structured interviews with process participants 49 workshops with core ADR-team, process owner, and process participants		
Case Insights	**Literature Insights**	**Solution Properties**
(CI1) KIPs display diverse control flows. (CI2) KIPs are heavily dependent on the context. (CI3) Data integrity issues hinder existing analysis and sharing approaches. (CI4) Lack of knowledge storage and no systematic knowledge distribution. (CI5) Limited data availability. (CI6) Process-related knowledge heavily depends on individual process participants.	(LI1) KIPs are difficult to standardize and to digitize. (LI2) Humans are the main source of complexity. (LI3) Knowledge development is often unplanned, unscheduled, and tied to the number of decisions in the process.	(SP1) The solution can deal with a high variability within the process and the corresponding data due to diverse control-flows and complexity. (SP2) The solution allows for adding and codifying knowledge in relation to the corresponding process. (SP3) The solution should enable systematic storing and distribution of the process-related knowledge.

Table 7
Evolution of Design Principles (I)

Iteration 1		**Iteration 2**	
Four confirmatory focus groups with a total of 13 process participants at Fluid Processing Ltd. Three workshops at Industrial Connectors Inc. with a total of nine process participants.		Two simulation games at Fluid Processing Ltd. with a total of nine participants. One simulation game at Industrial Connectors Inc. with seven participants.	
Artifact	**Insights Evaluation 1**	**Artifact**	**Insights Evaluation 2**
Conceptual IT Artifact (including an initial graphical user interface)	(E1.1) Necessity to integrate such a system into existing systems. (E1.2) Consequences and solutions of past process instances cannot be clearly defined yet, striving for the integration of a feedback loop. (E1.3) Provide reasoning on how the similarity of past process instances is defined. (E1.4) Guidance on knowing what to do with the gathered information about the KIP is necessary to proceed further. (E1.5) Implementation of recommended actions.	Prototypical IT Artifact	(E2.1) Focusing more on individual activities and distinguishing them is crucial. (E2.2) Consider the integration of Information from multiple sources. (E2.3) Due to diverse control flows and contents of KIPs, focusing on similar instances is essential. (E2.4) Recommended actions need to fit the role of participants and different organizational process goals. Further, the feedback loop was considered very useful. (E2.5) Currently relevant and responsible people that also act in the process should be included and displayed.

Table 8
Evolution of Design Principles (II)

<table>
<tr><th colspan="2">Iteration 3</th><th>Formalization of Learning</th></tr>
<tr><td colspan="2">One workshop with five practitioners of the core ADR team and one researcher of another working group.
Quantitative and qualitative feedback from nine practitioners and 14 researchers according to the criteria by Iivari et al. (2021).
Gather individual feedback on each proposition.</td><td>-</td></tr>
<tr><th>Propositions</th><th>Insights Evaluation 3</th><th>Design Principles</th></tr>
<tr><td>(P1) Identify knowledge-intensive activities and distinguish them from administrative ones.</td><td>(E3.1) Drawing a clear line between knowledge-intensive and administrative activities is difficult.
(E3.2) In order to perform process mining on KIPs, the relevant process and activities should be identified before.</td><td>/</td></tr>
<tr><td rowspan="2">(P2) Externalize tacit knowledge as unstructured data and relate it to specific process instances.</td><td rowspan="2">(E3.3) Highly important and very helpful.
(E3.4) It is important to focus in more detail on how to externalize and save the knowledge. This should simplify the conversion of tacit to explicit knowledge as well as avoid conversion loss.</td><td>DP1: Externalize Tacit Process-Related Knowledge to Information.</td></tr>
<tr><td>DP2: Enhance Event Log with Categorized Information.</td></tr>
<tr><td>(P3) Make knowledge from past process instances accessible.</td><td>(E3.5) As KIPs do not produce a huge amount of data, it is difficult to apply traditional process mining approaches.
(E3.6) P2 remains important to allow the application of process mining.</td><td rowspan="2">DP3: Retrieve Information from the Event Log through Process Mining</td></tr>
<tr><td rowspan="2">(P5) Derive actionable interventions.</td><td>(E3.7) Fostering the understanding and engagement of process participants through process mining insights is crucial for the success and impact.</td></tr>
<tr><td>(E3.8) It is important to internalize the information gathered through process mining to derive actions.
(E3.9) Clear definitions and previously defined goals are necessary.</td><td>DP4: Internalize Information to Create New Process-Related Knowledge.</td></tr>
<tr><td>(P4) Network knowledge carriers.</td><td>(E3.11) Well received and was considered novel and relevant, especially in large organizations.
(E3.12) Proposition 2 and 4 are complementary to each other.</td><td>DP5: Identify and Network Knowledge Carriers through Process Mining.</td></tr>
</table>

Table 9
Evolution of Design Principles (III)

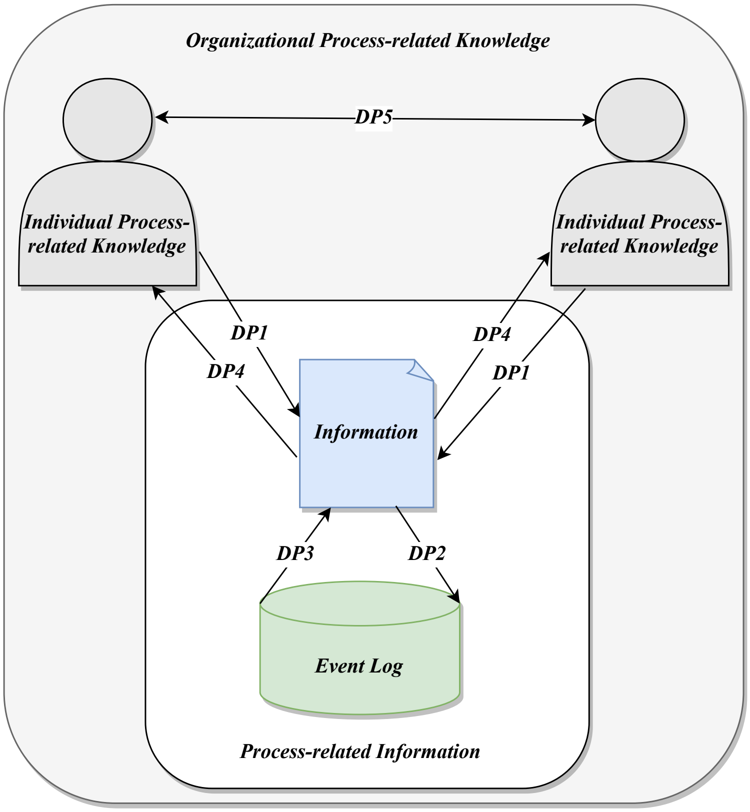

Figure 9: Illustration of the developed Design Principles

Design Principle 1: Externalize Tacit Process-Related Knowledge to 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	Write down knowledge as text, make a drawing from scratch, or add other documents that might exist but have not been made available to co-workers or the organization yet. Filter the "right" knowledge and relate it to the specific process instances so that it is visible which knowledge belongs to which process and to which instance to use it for process mining.
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: Enhance Event Log with Categorized 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 classifying 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 [57]. 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: 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 clustering). 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 [58]. Combining explicit knowledge from diverse sources is essential [20, 47], as even experienced participants struggle to overcome these biases when recalling similar past events.
Design Principle 4: 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, 47]. Our study found that the information presented to process participants during tasks significantly influences their performance in business processes.
Design Principle 5: Identify and Network Knowledge Carriers through Process Mining	
Implementer	IT Artifact & Process Analyst
User	Process Participant
Aim	To identify knowledge carriers 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 [51, 20, 47], yet knowledge carriers 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 10
Design Principles according to Gregor et al. [23]

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