Explaining Process Dynamics: A Process Mining Context Taxonomy for Sense-Making

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Abstract

Process mining research focuses on analyzing, visualizing, and predicting business process performance. However, the interpretation of process mining results often overlooks the critical role of context, limiting the ability to derive meaningful insights into process dynamics. In this paper, we develop a Process Mining Context Taxonomy that identifies and categorizes contextual factors influencing process mining outcomes across three levels: process-immediate, organization-internal, and organization-external context. Grounded in existing context frameworks and empirical insights from routine dynamics, the taxonomy provides a structured approach for incorporating context into process mining analyses. We demonstrate its applicability through a case study in a financial institution and evaluate its usability in a user study involving process mining experts. Based on these findings, we propose two usage paths to guide process analysts in interpreting process mining results. Our study highlights the need for contextualization in process mining, offers actionable guidance to enhance the interpretability of process mining efforts, and opens up promising avenues for future research.

Keywords: context, process mining, taxonomy, sense-making, dynamics

1 Introduction

Process mining research has primarily focused on developing algorithms to visualize, analyze, and predict the performance of business processes. While these objectives have been significantly enhanced by technical advances, recent research also stresses the importance of shifting attention toward managerial implications and organizational settings of process mining [1–5]. One critical but underexplored area is the role of context in making sense of process mining results [6, 7]. Although digital traces of process behavior allow for fine-granular insights into socio-technical phenomena [8, 9], data-focused process mining results alone do not inherently facilitate meaningful interpretations of the dynamics of business processes. Instead, contextual information is crucial to make sense of the situational idiosyncrasies surrounding a given business process [6].

For example, consider the study by Pentland et al. [10], where process mining analysis revealed considerable variation within a hospital's patient check-in process. While such variation might initially suggest inefficiencies, contextual analysis revealed that these dynamics align with seasonal flu-related adjustments, reflecting desirable, adaptive behavior. [10]. Similarly, IT-based changes in an onboarding process of a financial institution can affect how this process is performed over time, leading to intended but also unintended dynamics [11]. Such cases demonstrate that interpreting process mining results without contextual information risks misdiagnosing process dynamics, leading to inappropriate interventions. In short, contextual factors are crucial for correctly interpreting process behavior and deriving relevant actions.

However, identifying which contextual factors are important to explain the dynamics of business processes and systematically uncovering such knowledge remains elusive. Hence, our research addresses the question: *Which contextual factors have to be considered for making sense of business process dynamics in process mining results?* To answer this question, we leverage empirical findings from the field of routine dynamics, which has accumulated detailed and multifaceted explanations about dynamics and change in processes, typically based on inductive research designs, involving ethnographies and interviews. Notably, the concept of "routines" in routine dynamics corresponds closely to the notion of "business processes" in Business Process Management (BPM) [6, 12]. Thus, insights from routine dynamics research offer valuable perspectives for process analysts, shedding light on the contextual factors that drive the dynamics and changes observed in process mining results [10, 13–15].

In this paper, we develop a taxonomy [16] that organizes and structures contextual factors that are relevant for making sense of process mining results. We ground our research in two streams of literature: we integrate prior context frameworks from business process management with empirical insights from routine dynamics research [15, 17]. In doing so, we organize context around three levels: (1) process-immediate, (2) organization-internal, and (3) organization-external context. For each level, we provide a number of sub-dimensions. We demonstrate our taxonomy through a real-world application in a financial institution in Europe, and we evaluate its usefulness and ease of use by conducting a user study with 20 process mining experts. Based on the evaluation results, we also specify two usage paths and accompanying guiding questions to support the application of our taxonomy in research and practice.

Note that this paper is an extended and revised version of our earlier work on the role of context for making sense of process mining results [18]. In this paper, we extend our earlier work in three central ways: First, we systematically structure our methodological approach according to established taxonomy-development guidelines [16]. Second, we introduce the results of an additional evaluation of the taxonomy based on a user study with 20 process mining experts. Third, we leverage the insights from the user study to outline potential usage paths and guiding questions to support the application of the taxonomy.

The remainder of this paper is structured as follows. In Section 2, we outline the research background on managerial aspects of process mining, as well as the role of context in BPM and routine dynamics. In Section 3, we elaborate on the details of our methodological approach. Section 4 comprises the final Process Mining Context Taxonomy, before Section 5 demonstrates its application in a real-world case and Section 6 presents the results of a user study evaluation. In Section 7, we discuss two potential usage paths and accompanying guiding questions. Finally, Section 8 considers important implications, limitations, and opportunities for future work before Section 9 concludes the paper.

2 Research Background

2.1 Managerial Aspects of Process Mining

Process mining tools depict dynamics and changes of business processes on the grounds of event log data. Process discovery techniques, for instance, show the variety of process instances and the multiplicity of ways through which the process can be performed. Such results are typically used by process analysts who seek to gain insights into the process to take appropriate actions (e.g., to improve process runtime). So far, research on process mining has primarily focused on technical aspects [19, 20]. To this end, research has been concerned with the development and refinement of algorithms and analysis techniques for event log data.

Recent arguments have emphasized, however, that process mining yields implications that go beyond the established technical focus [3]. Along these lines, an emerging stream of studies sheds light on the managerial implications that occur, for example, in the adoption and management of process mining [1–5], the different organizational setups [21], the portfolio of process mining use cases [22], process mining readiness and capabilities [23, 24], or its value creation [25]. Process mining establishes high levels of transparency, which can benefit decision-making. One core challenge in this regard is that those who use process mining understand and interpret results in appropriate ways [1, 26]. Nonetheless, process mining results are by no means self-explanatory. For example, when process mining reveals that a given business process is performed in a variety of ways, there can be a number of different explanations for this variation [6, 10]. Hence, one should consider the conditions and circumstances in which a process is performed, i.e., their *context*.

2.2 The Role of Context in Business Process Management and Process Mining

Context can be defined as "the situation within which something exists or happens, and that can help explain it" [27]. Context has been considered in BPM research to stress how business processes are embedded in environments that impose certain requirements [17, 28–31]. Along these lines, the focus on context is considered to counter the "one-size-fits-all approach" that had been traditionally applied in BPM [32]. Taking on this view, one is expected to gain a better understanding of a business process by taking contextual features into account.

A few studies in the process mining field have accounted for context. Some studies have sought to explain why and how process mining results depict change and dynamics [33], how context can be captured to improve predictions made about ongoing process instances [7, 34] as well as to improve other process mining techniques [35, 36], or how it can be considered in the visualization of control-flow behavior [37, 38]. Furthermore, certain techniques have already tried to automatically infer context from event log data. For example, concept drift detection techniques have been applied to uncover change points to the underlying process, which can be indications for contextual changes [39]. Overall, however, contextual explanations have neither been the focus of such studies nor have they been generated in systematic ways.

More systematic approaches to understanding the role of context in process mining and BPM have been developed through *context frameworks*. In relation to process mining, van der Aalst and Dustdar [30] suggest how process mining techniques can consider context by mining additional context types, including *instance context*, *process context*, *social context*, and *external context* [30]. Their key argument is that process mining analysis is more comprehensive when event log data and process mining techniques reveal more information about the conditions in which specific process executions were performed. Furthermore, in the context of process modeling and design, Rosemann et al. [17] argue that context can be categorized along layers that differ in their proximity to the business process; for instance, the *internal layer* entails components that are directly involved in the performance of a business process, including questions such as what is the model or who is involved; the *environmental layer*, in contrast, comprises broad factors that can have an indirect influence on a process, such as ecological factors. In a similar vein, the framework by vom Brocke et al. [28] distinguishes between dimensions that highlight how the process is performed. For example, the *process dimension* distinguishes between the frequency in which a process occurs and the degree to which it should vary; the *organization dimension* distinguishes between the size of the organization and the industry in which a given organization is located. As such, each context framework serves a distinct purpose, focusing on different aspects of business processes. However, none of them are specifically designed to facilitate sense-making of process mining results or to capture and explain the dynamics inherent in process executions.

Figure 1 shows a comparison of these three BPM context frameworks with our developed Process Mining Context Taxonomy. Aside from the main focus, broad dimensions, and application scenarios of each framework, we also highlight how well they address key requirements for making sense of process mining results. We derived

Framework	Focus	Broad dimensions	Application scenario	Requirements
vom Brocke et al. (2016)	BPM initiatives	Goal, process, organization, and environment	Clarifying the context surrounding a business process to plan BPM initiatives	R1 (+) R2 (+)
van der Aalst & Dustdar (2012)	Context data	Instance, process, social, and external	Deciding which types of data should be included in the analysis	R1 (+) R2 (+/-) R3 (+)
Rosemann et al. (2008)	Process modeling and design	Immediate, internal, external, environmental	Understanding contextual dimensions that influence the design of business processes	R1 (+) R2 (+/-) R5 (+/-)
Process Mining Context Taxonomy (this study)	Sense-making of process mining results	Process-immediate, organization-internal, organization-external	Interpreting dynamics and changes within process mining results	R1 (+) R2 (+) R3 (+) R4 (+) R5 (+)

Fig. 1 Comparison of Existing Context Frameworks in BPM

the requirements from Zimmermann et al. [40], who conducted a series of interviews with 41 process mining analysts to identify challenges encountered during process mining analysis. Their study identified 23 challenges, which were categorized according to the respective phases of a process mining project [40]. We further enriched these challenges with empirical insights gained from our case study to formulate the following requirements:

R1. ***Multi-level***: The context taxonomy should distinguish between different levels of context.

R2. ***Scoping***: The context taxonomy should support analysts in defining the scope of process analysis initiatives by identifying relevant contextual factors.

R3. ***Data integration***: The context taxonomy should enable linking contextual factors to event data represented in process mining results.

R4. ***Sense-making***: The context taxonomy should enable analysts to interpret process mining results by systematically identifying context factors that have an influence on the business process.

R5. ***Dynamics***: The context taxonomy should help analysts to explain observed variations and changes within a business process.

We substantiate how our Process Mining Context Taxonomy addresses these requirements in Section 5 and Section 6. To cover these requirements in our taxonomy, we build on research on routine dynamics, which we outline in the following section.

2.3 The Role of Context in Routine Dynamics Research

In the organization sciences, context has been used to *make sense* of and thoroughly explain the dynamics of processes [6, 15]. Studies on *routine dynamics* seek to understand *why* and *how* processes dynamically change over time [6, 10, 41]. Crucially, while these studies speak about *routines* as their focal phenomenon, they refer to business processes [6, 10, 12]. Hence, findings from routine research are not only applicable to the study of business processes, but they can also reveal new insights and explanations [10, 12].

Across a plethora of empirical studies—primarily based on longitudinal, inductive research designs, involving ethnography and interview methods—routine dynamics research has developed a variety of context-based explanations for process dynamics. For instance, context has been used to explain changes in process dynamics with respect to seasonal changes [42], such as when the flu season forces hospital staff to align their processes [10]; to explain how workers in a company intentionally adjust their processes to compensate for resource constraints [43]; or to show that processes are performed differently whenever certain stakeholders, such as higher-status managers, are involved [44]. Typically, such context-based explanations emerge as researchers are deeply embedded in a given organization and gradually 'come to see' the relevant factors. The procedure to identify context is, thus, dependent on inductive case-specific theorizing and can take months or even years.

When analysts make sense of process mining results, there needs to be a middle ground: Context should be *systematized* to the extent that it can guide and inform sense-making in quick and reliable ways; yet, such a systematization should be based on dimensions and factors that are relevant and widely applicable to all kinds of settings when business processes exhibit dynamics and change.

3 Research Design

To enable sense-making of process mining results, we consider and integrate research on routine dynamics research as well as BPM and process mining-related research [12]. To develop and conceptualize our findings, we leverage a taxonomy development approach. Specifically, we rely on the guidance offered by Kundisch et al. [16], which builds on and extends the approach of Nickerson et al. [45]. Both of these approaches represent established taxonomy development guidelines within the information systems field. The extended taxonomy design process (ETDP) of Kundisch et al. [16] comprises six phases that guide our taxonomy development: (1) identify problem and motivate, (2) define objectives of a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication. The entire ETDP is presented in Appendix C here: https://tinyurl.com/2a6kffru. First, we carved out the problem that we intended to address as well as the purpose of our taxonomy in the Introduction and Research Background sections of this study (c.f., Phase 1: 'Identify problem and motivate' in [16]), before defining the meta-characteristic, ending conditions, and evaluation goals of our taxonomy (c.f., Phase 2: 'Define objectives of a solution' in [16]). To summarize our objectives, we were interested in pursuing the following questions:

- What kinds of changes and dynamics can occur in business processes?
- How can these dynamics in business processes be explained?
- To what extent can these explanations be generalized as contextual factors for process mining results?

3.1 Meta-Characteristic and Ending Conditions

To guide our taxonomy development and to identify appropriate characteristics, we follow Nickerson et al. [45] and Kundisch et al. [16] by specifying a meta-characteristic of our taxonomy. In line with the purpose of our taxonomy to integrate contextual considerations into the interpretation of process mining results, the meta-characteristic of our taxonomy is defined as 'Dimensions of business process context in process mining'. To ensure that our taxonomy achieves the aspired quality standards and to facilitate the iterative nature of the development process, we determined objective as well as subjective ending conditions. Our objective ending conditions follow from the set of conditions proposed by Nickerson et al. [45] and they pose that: (1) all levels and dimensions are unique and non-redundant; (2) at least one object is classified under every dimension of every level; (3) no new levels or dimensions were added in the last iteration; (4) no levels or dimensions were merged or split in the last iteration. Our subjective ending conditions are also adopted from Nickerson et al. [45] and they state that a taxonomy has to be: concise, robust, comprehensive, extendible, and explanatory to (subjectively) terminate the development process. In addition, Kundisch et al. [16] also propose the formulation of evaluation goals to align problem and solution space. We determine three goals for the evaluation of our taxonomy: The levels and dimensions of the taxonomy should support users with the interpretation and sense-making of process mining results by allowing them to (1) *describe* the context of process mining results, (2) *identify* relevant contextual dimensions and trajectories for further analysis, and (3) *analyze* and prioritize their respective importance.

3.2 Design and Development, Demonstration, and Evaluation

Our taxonomy development approach consisted of four iterations in total: two design and development iterations (c.f., Phase 3: Design and Development in [16]) following a conceptual-to-empirical and an empirical-to-conceptual approach, one demonstration iteration (c.f., Phase 4: Demonstration in [16]) following an empirical-to-conceptual approach, and a final iteration consisting of an evaluation (c.f., Phase 5: Evaluation in [16]). To summarize, our approach included the following steps: (1) We synthesized research from BPM and routine dynamics to develop an understanding of context levels and dimensions and conceptualize an initial taxonomy. (2) We systematically reviewed and coded articles on routine dynamics to validate and refine our context taxonomy in light of a broader range of empirical studies of process dynamics. (3) We demonstrated the taxonomy based on a real-world use case. (4) We evaluated the use of the taxonomy with 20 process mining experts from academia and practice. We describe these four iterations in detail below.

First design and development iteration. As a first step, our goal was to develop an initial taxonomy for making sense of process mining results, including broad context levels and more specific dimensions. We adopted the principles of a narrative review methodology [46]. As argued before, the two literature streams—BPM and process mining, as well as routine dynamics—overlap in the phenomenon they are studying (dynamics of business processes) while pursuing complementary research [12]. Hence, we based the development of our taxonomy on phenomenon-driven theorizing [46]. To this end, we purposefully selected and considered conceptual and empirical studies in BPM and process mining, as well as routine dynamics research that offer contextual explanations for changes and dynamics of business processes, which can be applied to sense-making of process mining results. In doing so, we leveraged the multi-disciplinary competences of the authors of this paper, who have research backgrounds in BPM, process mining, and routine dynamics research.

We considered findings from BPM and routine dynamics research and then mapped them to existing context frameworks [17, 28–31]. As argued in Section 2.2, existing context frameworks already point to several contextual factors primarily intended for the development of process mining techniques and the design of business processes. Furthermore, we included illustrative studies in the field of routine dynamics, which offer explanations of process dynamics at different scales and in light of different contextual influences, e.g., [10, 15, 43, 44]. In an iterative process, we discussed which context dimensions may broadly affect process dynamics and how contextual explanations in empirical studies do or do not align with context dimensions.

Across this process, we searched for patterns across existing frameworks and reflected those against our interest in studying dynamics and change of business processes. Thereby, we kept specific elements and components of existing frameworks while we omitted others that could not be directly related to sense-making of process mining results. For example, existing context frameworks entail a process dimension that refers to components of a business process, such as resources or activities [17, 28, 30]. Since previous findings in BPM research and routine dynamics research have shown that this dimension can be crucial to explain process dynamics over time [33, 43], we kept this dimension in our taxonomy. At the same time, we excluded dimensions that may be relevant to the design of a given business process (e.g., in terms of performance metrics) but are irrelevant to making sense of dynamics and change of business processes; an example is *capital providers*, which is an external factor in the framework by Rosemann et al. [17].

In this first iteration, we agreed that sense-making of process mining results can cover three broad levels: *process-immediate context, organization-internal context, and organization-external context*. Furthermore, we asserted that each level entails several sub-dimensions. For instance, we suggested that the process-immediate context may be decomposed into *activity-related aspects* or *resource-related aspects*, whereas organization-internal context may include *intra-organizational dynamics* and *structural aspects*.

Second design and development iteration. In the next step, we systematically searched for and reviewed empirical studies on routine dynamics. The goal of this step was to validate and, if necessary, adjust the taxonomy's context dimensions in light of a broader range of empirical studies on routine dynamics.

As we searched for and selected relevant articles, we followed the guidelines for systematic literature reviews by vom Brocke et al. [47]. After defining the scope and key concepts (i.e., routine dynamics), we searched the SCOPUS database for all articles that use "routine dynamics" in their title, abstract, or keywords, published until June 2, 2024. This search led to 120 hits. Subsequently, we screened all papers and excluded those not concerned with contextual explanations of routine dynamics, or those that do not relate to routine dynamics at all. This led to a set of 52 remaining articles. Forward and backward searches yielded an additional 13 articles, leading to a final set of 65 articles.

Afterward, we systematically coded all articles using the dimensions from the initial taxonomy as developed in Step 1. We focused on the specific perspective(s) through which routine dynamics studies explain and make sense of dynamics and change in business processes. We applied a mix of deductive and inductive coding. On the one hand, we used the levels and dimensions generated in the first iteration to sensitize us towards contextual explanations. On the other hand, we remained open to results that could not be subsumed by our initial taxonomy; in such cases, we refined categories or aimed to develop new ones. Along these lines, we also considered empirical studies from the BPM and process mining research to the extent that they revealed contextual explanations [7, 48–50].

Over the course of this step, we refined several context dimensions of the taxonomy. For instance, the initial taxonomy described that one dimension at the organization-internal level refers to "organizational idiosyncrasies", referring to the specific characteristics of an organization where a business process is performed. In the validation, we changed this dimension to *identity-related aspects* to include a broader array of contextual explanations, including those related to strategy and culture [51]; similarly, we changed the dimension "structural aspects" to *structural and procedural aspects* to allow for a broader integration of contextual explanations.

An overview of all reviewed articles and the final coding can be found in Appendix A here: https://tinyurl.com/2a6kffru.

Demonstration. After both design and development iterations, we demonstrate the application of our taxonomy with a real-world case of a customer onboarding process at a financial institution. Specifically, we show three different examples of dynamics that were identified with process mining, and we show how our taxonomy can guide context-based interpretation of those results to achieve meaningful insights. One objective of a demonstration, according to Kundisch et al. [16], is to ensure "that a taxonomy is formally valid and satisfies the definition of a taxonomy independently of its purpose(s) and target user group(s)" (p. 432). Hence, with the real-world application, we demonstrate (ex ante) that the current version of the taxonomy fulfills the necessary (e.g., 'is it a taxonomy?') as well as the sufficient (e.g., 'is it an applicable taxonomy?') conditions [16]. In addition, our demonstration also showcases how the taxonomy can yield useful and valuable contextual insights for the interpretation of process mining results within a practical setting. The demonstration of our taxonomy with the real-world case of a customer customer onboarding process at a financial institution is described in more detail in Section 5.

Evaluation. In the fourth iteration, we evaluated our developed taxonomy with 20 participants in a user study to assess the predetermined evaluation goals of describing, identifying, and analyzing context for process mining. Following design science research evaluations [52], Kundisch et al. [16] state that such an ex post evaluation should assess the usefulness of the taxonomy (e.g., 'is it a useful taxonomy?'). Specifically, it is important to determine how well the target user group can use the taxonomy to achieve the intended purpose(s). The target user group, and thus also the participants of our user study, comprised process mining experts from academia and practice, who were tasked to interpret process mining results with and without our taxonomy. The overall procedure of our user study is illustrated in Figure 2, where gray parts indicate user input. The complete design of the user study in Qualtrics is presented in Appendix B here: https://tinyurl.com/2a6kffru.

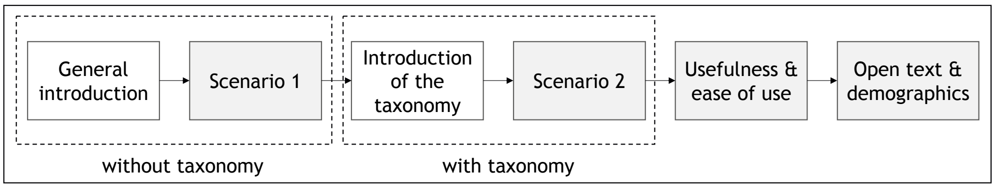

Fig. 2 Procedure of the User Study

The user study started with a general introduction of the research team and the background of the study, before continuing with the first process mining scenario from an onboarding process in a financial institution. After briefly introducing this process and respective KPIs, the participants completed a task, where they were asked to come up with plausible explanations or directions for different observations that were made during process mining analysis. For example, an observation could constitute the fact that a lot of variance in the throughput time of the process was detected over a period of several months. The task for the participants was, then, to formulate how this variance could be plausibly explained. After completing this first task for scenario 1, we introduced the Process Mining Context Taxonomy by describing the individual levels and dimensions. Subsequently, the participants were briefly tasked to allocate the dimensions to the respective levels as a manipulation check. Then, the participants completed the same set of tasks for the second process mining scenario, which was based on an event log of a hospital and their handling of sepsis patients [53].

After completing the tasks for both scenarios, one time with and one time without the taxonomy, the participants provided quantitative as well as qualitative feedback regarding the use of the taxonomy. The quantitative evaluation relied on the established survey items from the technology acceptance model [54] to measure usefulness and ease of use on a 7-point Likert scale. The qualitative evaluation allowed participants to also provide feedback in open text form to address how they used the taxonomy as well as potential benefits and challenges. Lastly, we collected demographic information of the participants regarding their expertise in process mining (in years), their field of industry, and their roles. The results of our evaluation are described in Section 6. The following section presents the resulting Process Mining Context Taxonomy.

4 Process Mining Context Taxonomy: Context Levels and Dimensions

Our taxonomy consists of three context levels: *process-immediate*, *organization-internal*, and *organization-external*. Each level comprises three dimensions to make sense of process mining results. Considering findings from research on BPM, process mining, and routine dynamics research, these dimensions can be linked to different sources. While some sources are more related to social dynamics (such as learning dynamics or policy changes), others can be associated with technical problems (such as changes in data standards). The Process Mining Context Taxonomy is depicted in Figure 3. In the following, we describe each context level and its respective dimensions.

Process-immediate context. This context level refers to what is happening in the actual process, that is, the underlying, interrelated sequence of activities and events. This dimension is based on the observation that retention, variation, and selection of specific activities in a process, as well as when and how they are performed, can lead to process dynamics and change [41, 55]. We adopt this category from existing frameworks [17, 32] and add three dimensions that are relevant to make sense of process mining results:

Activity-related aspects describe how changes and dynamics can be directly related to executing activities in the process. When activities are removed or changed, process participants may need time to learn and unlearn [56]. Also, some activities might become less relevant and occur less frequently over time without any intentional intervention [57].

Resource-related aspects refer to resources involved in the process, such as process participants or information technology. Availabilities [58] and workarounds [59] are shown to the extent that they are covered in event logs. Dynamics in a process can be related to a worker who becomes unavailable and needs to be replaced, potentially leading to improvisation and temporary confusion [43]. Resources may be more or less available at a given point in time, prompting process participants to find ad-hoc workarounds and temporary deviations [48].

IT system features refer to adaptations or modifications of process-related IT systems. As almost all work-related activities are performed with or mediated by IT systems [60], such changes directly impact how business processes are performed. Since the functionalities of such systems can change over time [61], this dimension considers corresponding dynamics in business processes. These can occur, for instance, when IT systems introduce new features that restrict traditional work practices [13]. Technical problems, such as when new features in an IT system do not work properly, can create a backlog and lead to dynamics in the process [11, 62].

Level	Dimension	Description	Examples
Process-immediate context	*Activity-related aspects*	Changes in the sequence of activities and events	• Activities are removed, added, or changed • Participants learn and forget
	Resource-related aspects	Changes in the availability of resources	• Process participants are absent, prompting improvisation • Resources are unavailable, leading to workarounds
	IT system features	Changes and issues in IT systems	• New features disrupt established work processes • Technical problems lead to backlog
Organization-internal context	*Intra-organizational dynamics*	Dynamics within organizational boundaries	• Social learning in a group • Process improvement initiatives
	Structural and procedural aspects	Changes in the organizational set-up	• Changes in roles • Changes in resource assignments
	Identity-related aspects	Shared understandings and related practices	• Specific approaches for case handling • Self-developed IT infrastructure
Organization-external context	*Environmental dynamics*	Changes in the environment	• COVID-19-related disruptions • Seasonal changes
	Inter-organizational relations	Relations between organizations	• Changes in coordination patterns • Resource delays
	Regulations, policies, and laws	Guidelines affecting business processes	• Privacy regulations affect data processing • Compliance rules change process flexibility

Fig. 3 Process Mining Context Taxonomy

Organization-internal context. This context level subsumes contextual factors that occur within the boundaries of an organization, thereby creating a direct influence on a business process. This level is informed by empirical research that has found how organizational dynamics, such as changes in roles [63] or leadership styles [44] can impact the ways processes are being carried out. The organization-internal context level is based on integrating existing context levels, such as the *internal layer* in [17] and the *organization dimension* in [32]. We specify three related dimensions that are relevant for sense-making of process mining results:

Intra-organizational dynamics refer to dynamics and changes inside the organization where the business process is performed. This can be based on social learning when members of the organization work together over time and learn to anticipate each other's actions and decisions; this has been associated with efficiency gains in a process over time [63]. Another example is the use of an employee Wiki in which organizational members share best practices and find better means to perform a business process over time [64]. Intra-organizational dynamics can also manifest as interdependencies when improvements or changes in one business process affect how another business process is performed over time [65].

Structural and procedural aspects refer to an organization's structural set-up as it influences a given process, such as hierarchies. Process dynamics typically occur when such structural aspects are changed. For example, re-assignments of roles and responsibilities can lead to confusion among process participants and longer throughput times [63]. Dynamics can also be caused by changes in resource assignments [49] or changes in IS-based task assignments.

Identity-related aspects refer to values and shared understandings, as well as associated conventions and practices that are specific to a given organization [66]. For instance, an organization may have distinct internal guidelines on how certain cases should be handled and prioritized [44, 67]. Identity-related aspects can also be reflected in (e.g., self-developed) IT infrastructures that necessitate specific process behavior [68].

Organization-external context. This context level subsumes contextual factors that lie outside the boundaries of an organization but can still have a direct impact on how business processes are performed. This level became evident, for instance, during the COVID-19 pandemic, when organizations were forced to adjust their operations. The organization-external context level integrates dimensions from prior frameworks, such as the *environment dimension* from [32] and the *external layer* from [17]. The following three dimensions are relevant for sense-making of process mining results:

Environmental dynamics can have a direct impact on business processes when such dynamics inhibit the way in which processes are usually performed. For instance, changes in demands during the COVID-19 pandemic made specific process outcomes more or less desired [69]. Also, seasonal fluctuations can lead to changes in resource availabilities, which, in turn, can change the performance of business processes [48].

Inter-organizational relations refer to relations between organizations, such as when their business processes are tightly linked. Dynamics can be caused when organizations have different coordination patterns (or one of them changes the pattern) [70], leading to irregularities in timing. Delays in resources can, in turn, cause delays to certain process executions [71].

Regulations, policies, and laws refer to external constraints that can influence the ways a business process can or should be performed. New privacy regulations, for instance, may impose limitations on how customer data can be used [50]. Also, new compliance regulations can enable or restrict the flexibility of a business process [17]

5 Demonstration of the Taxonomy

To demonstrate our taxonomy, we draw from real-world data from a customer onboarding process in a European financial institution. The depicted process mining results illustrate the position of a process analyst who does not know what is going on and needs to make sense of observable dynamics. Hence, the following examples should showcase how our taxonomy can be used in such situations.

The financial institution employs around 200 people and offers services for corporate clients, private clients, and funds, who are mainly located in Europe. It stands out from its competitors by offering innovative solutions, such as blockchain banking, and providing its customers with digital tools for completing their banking activities. The following example refers to the customer onboarding process of this bank. This process covers the entire customer onboarding, starting with the first request to open a bank account via the website and ending with the actual opening of a customer's account. This process is supported by an internally developed tool that guides account managers through the process steps. As a result, we could collect event log data for all end-to-end process executions. We captured and analyzed these traces over a period of two years. In total, we analyzed 901 cases starting from March 2020, which included over 32.000 activities.

In doing so, we adopted the complexity measure of [41, 72], which estimates the total number of ways through which a process can be performed from source to sink at a given point in time[1]. Complexity is a common measure to compute variations in a business process [73]. When analyzing this measure for the customer onboarding process over two years, we find that the complexity of the process dynamically changes over time. For instance, as depicted in Figure 4, we can see large variations (around July 2020) and smaller variations (around July 2021), which indicate that something in the process changed.

When we seek to explain these dynamics, however, we are confronted with the problem outlined at the beginning of the paper: Process mining results alone are not sufficient to explain *why* and *how* a process changes over time. The dynamics in the customer onboarding process, for example, leave room for a variety of explanations. A sharp increase in process complexity could indicate (1) process inefficiencies, (2) workarounds, or (3) desired flexibility, among other things. Therefore, contextual insights are necessary to make sense of these dynamics and plan appropriate improvement initiatives.

Drawing from our taxonomy, we systematically enrich the process mining results with context-based sense-making. We demonstrate this in three examples. Figure 4 depicts selected snippets of dynamic changes of the complexity measure. We focus on the variations highlighted in red, which represent contextual changes in and around the process. Combining the visualized results from process mining with qualitative data (i.e., interviews), we highlight different levels and dimensions of our taxonomy:

[1] Hærem et al. (2015) [72] propose various methods for calculating complexity based on network size. For a detailed explanation and calculations, we refer interested readers to the supplementary materials (Appendix A–D) of their paper.

process-immediate (IT system features), organization-internal (structural and procedural aspects), and organization-external (inter-organizational relations) contextual changes within the customer onboarding process.

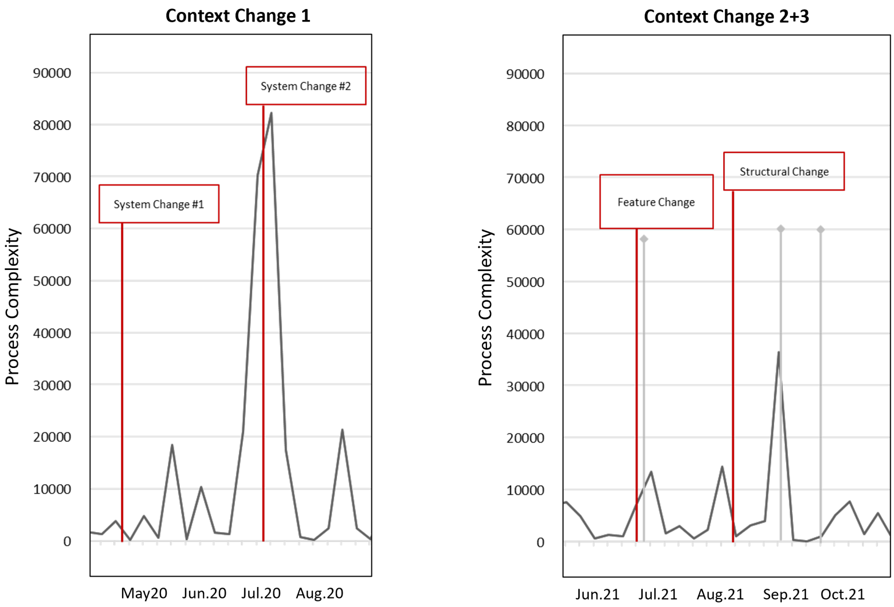

Fig. 4 Snippets of Process Mining Results of the Customer Onboarding Process

Demonstration 1: Process-immediate Level/IT System Features. The first contextual change we illustrate refers to a change in the organization's IT system and is depicted on the left side of Figure 4.

Inspecting the computational measure for process complexity in June and July 2020, we notice a considerable spike. Through interviews with employees, we found that during this period, the organization changed the information system for the customer onboarding process (System Change #1). It was decided that a new questionnaire would be sent out to customers automatically to collect customer data. However, due to inadequate testing, the new questionnaire could not be retrieved from the application environment, which led to errors when the account managers tried to carry out the respective process step. As a result, error messages caused by bugs in the system environment lead to deviant process performances (i.e., workarounds). This happened because process participants sought to continue with the process despite malfunctions in the system. Furthermore, process participants continuously contacted IT staff, who had to resolve each case manually. This caused a large backlog of cases. In the subsequent System Change #2, this issue was fixed by automating the manual assignment for ongoing cases and systematically solving the retrieval issue for new cases. This reduced the complexity of the process.

Taken together, this example shows how process mining results can be explained through the *process-immediate level* and, more specifically, changes in *IT system features*. Furthermore, this example also demonstrates how requirement 3 (data integration), which is derived from challenge 14 from Zimmermann et al. [40] and presented in Section 2.2, is fulfilled by the taxonomy, since the data gathered from interviews and incident tickets have now been linked to the event data to make sense of the process mining results.

Demonstration 2: Organization-internal Level/Structural and Procedural Aspects. The second contextual change we present is depicted on the right side of Figure 4. Looking at the results, we observed a significant increase in process complexity between August and September 2021. However, it was unclear which of the deployments or process changes were decisive for this since there were three process changes (one structural change and two other interventions) around this time.

Through interviews with users and developers, the increase in complexity could be explained by an organizational change initiative deployed three weeks before the spike, which included the reorganization of the front departments. This reorganization changed the roles and responsibilities within the process. Whereas previously, two people had worked on a case (the relationship manager and the assistant), the process was now carried out solely by one account manager. As a result, users were given new tasks, some of which were unrelated to the customer onboarding process. It took some time for users to adjust to these changes, which explains the delay in the spike. Initially, introducing new tasks caused confusion and uncertainty among the account managers, leading to a trial-and-error approach and resulting in deviant process executions. This caused a significant increase in process complexity as account managers tried to carry out the process. However, the complexity decreased as users became more familiar with their new tasks and utilized the provided training programs. In brief, this demonstration reflects how process mining results can be explained through changes at the *organization-internal level* and in terms of *structural and procedural aspects*. Furthermore, it shows how requirement 4 (sense-making), introduced in Section 2.2, is addressed, as the taxonomy supports the interpretation of process mining results by enabling the systematic identification of contextual factors that exert an influence on the business process.

Demonstration 3: Organization-external Level/Inter-organizational Relations. Lastly, we describe the dynamics visible at the end of June 2021, as visualized on the right side of Figure 4. Analyzing the process complexity measure, a sudden increase is evident. On a closer look, this was related to an initiative that intended to implement a process automation. At first, this increase could not be explained. It could be clarified, however, through the collection of contextual insights, in particular through interviews with the lead developer as well as the analysis of incident tickets.

The initiative aimed at automating the background screening process for customers to identify negative entries or political exposure. This was done by connecting the database and search function of an external service provider through an API, which then conducts a background check. However, the search was unsuccessful due to technical difficulties. The external service provider could not be involved, which hampered the inter-organizational coordination between the case organization and the external organization. Since the API connection did not deliver the desired outputs, users had to manually repeat the step. For instance, they searched for workarounds, which led to an increase in process complexity. This error was ultimately caused by inadequate communication between the external service provider and the organization but could be rectified shortly after the error occurred. Hence, the complexity decreased again. Taken together, this example shows how process dynamics can be explained through the *organization-external level* and changes in *inter-organizational relations*. Furthermore, it demonstrates how requirement 5 (dynamics), introduced in Section 2.2, is fulfilled, as the taxonomy supports analysts in explaining observed variations and changes within a business process.

6 User Study Evaluation

As outlined in Section 3, our methodology follows the ETDP of Kundisch et al. [16], suggesting the evaluation of the Process Mining Context Taxonomy in the fourth iteration. We conducted a user study with 20 process mining experts (11 practitioners and 9 academics), who are familiar with analyzing and interpreting process mining results to assess the ease of use and usefulness of the developed taxonomy. The participants, on average, had more than five years of experience in the process mining sector and were drawn from a diverse range of industries, including finance, energy, and technology. The median completion time for the user study was 65 minutes. The survey procedure is described in Section 3.2 and shown in Figure 2. An overview of the results and participants of the user study can be found in Appendix B here: https://tinyurl.com/2a6kffru.

After carrying out the tasks with and without the Process Mining Context Taxonomy, the participants assessed the survey items for usefulness and ease of use proposed by [54] on a 7-point Likert scale. A high rating for usefulness and ease of use suggests that the taxonomy supports process mining analysts in making sense of process mining results. The results of this quantitative evaluation are summarized in Figure 5.

We find that both usefulness and ease of use are rated high by the participants, with a mean of 5.43 and 5.74 respectively. These ratings were also consistent for both practitioners and academics, and we found no notable difference in their respective ratings. At the same time, we also found that the scores do not differ significantly with increasing experience in the field of process mining and that experts with more than 10 years of experience in the field of process mining also rate the taxonomy as useful and easy to use (e.g., E1, E8, E20). For ease of use, the ratings are distributed evenly, while being more concentrated around the mean for usefulness. While the average ratings for ease of use are consistently favorable, it is noteworthy that one user has assigned the lowest possible score to usefulness, indicated by the outlier in Figure 5. However, in the qualitative feedback the expert commented, that *"especially when there are multidimensional factors surrounding the information, I can see it being useful"* (E7). This corroborates requirement 1 (multi-level) for making sense of process mining results which is introduced in Section 2.2. Since this example constitutes the only negative outlier, we can conclude that the Process Mining Context Taxonomy is mostly considered to be useful and easy to use, warranting more detailed qualitative inquiry.

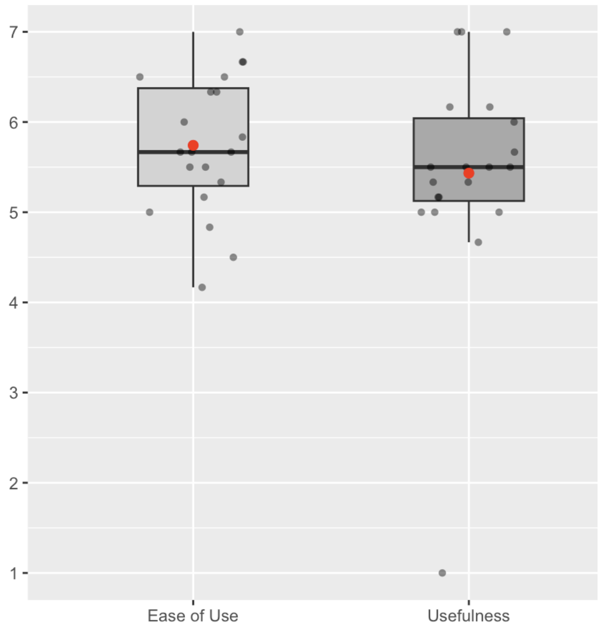

Fig. 5 Boxplot of Perceived Usefulness and Ease of Use

In addition to the quantitative assessment, the process mining experts also provided qualitative feedback in the form of open text responses. It was noted by several participants that the taxonomy assisted in identifying additional, previously unconsidered, dimensions, allowing process mining analysts to *"systematically examine each dimension, which felt much more comprehensive"* (E13) and *"classify the interpretation in a direct effective manner"*, as participant E9 mentioned.Multiple experts reported that the taxonomy is especially helpful to use as a checklist, providing *"more clarity and guidance on how to proceed and what to look for"* (E1) and ensuring that no potential effects are left unexplored. For some experts, it led to the discovery of entirely new dimensions they *"normally wouldn't have thought about, so it increased the search space for a solution"* (E17). Similarly, E5 reported that the taxonomy enables the user to check different levels, which *"could reduce biases"*. Another aspect addressed by E12 is the enhancement in quality that is associated with the utilization of the taxonomy, because *"structuring the changes and causes in a framework improves the quality extremely"*. Moreover, E16 reported, that the taxonomy serves as a *"good overview of potential starting points"*, thus supporting in the scoping of the analysis and addressing requirement 2 (scoping), which is based on challenge 1 in Zimmermann et al. [40].

Besides positively evaluating the usefulness and ease of use of the Process Mining Context Taxonomy, participants in our user study also provided feedback and opportunities for improvement regarding the specific ways in which the taxonomy can be applied. We can summarize this feedback with two key take-aways. First, we found that a systematic, structured way of applying the taxonomy would provide helpful guidance for users and aid them in uncovering contextual explanations for dynamics in business processes. Participants were, for example, looking for *"a guideline on how to apply it"* (E16) or *"a step-by-step solution that asks questions and guides the user through a process until the most likely "context influence" is identified"* (E10). Moreover, one process mining expert (E1) mentioned that the extensive taxonomy leads to a *"contextual overload"* making it difficult to prioritize the right area for improvement. For some, the dimensions were not readily apparent, necessitating a more prolonged period of familiarization with the taxonomic classification: *"The broader levels were quite easy to use and made it easier to check for each of those categories. However, the dimensions were not always clear and it increased the time to map those dimensions specifically"* (E5). Second, we found that it would be beneficial to provide users with a set of guiding questions or recommendations that can initiate further directions for analysis. Participants, for example, noted that *"it could be enhanced by some analysis recommendations"* (E19). Taking these points into consideration, we discuss how our taxonomy can be used below.

7 Discussion: Usage Paths for the Process Mining Context Taxonomy

While the Process Mining Context Taxonomy can be used to make sense of process mining results, it will not lead to immediate insights on its own. Importantly, the contextual knowledge itself is not provided by the taxonomy. Rather, the taxonomy enables triangulation by shifting attention to specific sources of dynamics and guiding further interrogation, data collection, and analysis to inform or validate assumptions. This triangulation is based on an abductive sense-making process [74, 75] that aims to iteratively obtain enough (contextual) information to be able to make confident decisions based on process mining results. In order to further specify how the context taxonomy can be used, we outline two general scenarios, or *usage paths*. They are depicted in Figure 6.

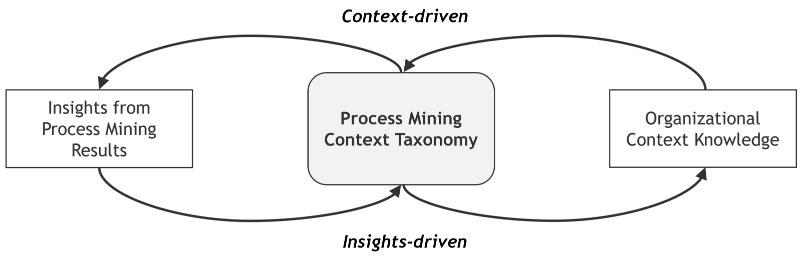

Fig. 6 Usage Paths of the Process Mining Context Taxonomy

On the one hand, the left loop depicts the *insights-driven usage* path. It assumes that the sense-making process is initiated by identifying interesting or surprising patterns in the data and then using the taxonomy to search for contextual explanations. The path starts by assessing process mining results and, then, systematically using the Process Mining Context Taxonomy to make sense of them and guide further analyses. For example, process analysts might initiate their analysis by starting with cues that they observe within the process mining results. After discovering irregularities or dynamics in the results, they consult the Process Mining Context Taxonomy to investigate which contextual levels and dimensions were at play during the time of interest. Then, after gathering the necessary organizational context knowledge, the analyst conducts further deep-dive analyses to consolidate her explanations, continuing this iterative cycle until enough information is obtained to make confident decisions. Specifically, an analyst might use concept drift detection techniques to identify change points, but without the right contextual knowledge, these changes remain unexplained. Here, the Process Mining Context Taxonomy provides a structured way to interpret and understand these detected changes by linking them to relevant contextual factors. Following this usage path, an analyst can ask the following questions to structure their contextual analysis with the Process Mining Context Taxonomy: 'Are there any unexpected dynamics within the process mining results?', 'Can you imagine that these dynamics have something to do with a change in activities, resources, or IT systems (process-immediate context)?', 'Is it possible that changes in other processes, structural changes, or idiosyncratic practices (organization-internal context) lead to these dynamics?', 'What environmental, inter-organizational, or regulatory changes (organization-external context) could be at play?', 'Where could you obtain the necessary context information?', and 'Which further analyses are necessary to gather more information about the relevant context?'.

On the other hand, the right loop reflects the *context-driven usage* path. Here, the sense-making process starts with a priori knowledge about contextual changes within the organization that might affect the business process. Such knowledge, if not available already, has to be acquired by, for example, interviewing experts within the organization or screening environmental conditions. The Process Mining Context Taxonomy, in turn, helps to classify these changes and initiate tailored process mining analyses to further explore the contextual change. For instance, a process analyst might start her analysis with a priori knowledge about context changes that occurred recently, such as a structural change within a department. With this knowledge in mind, the analyst consults the Process Mining Context Taxonomy to assess which levels and dimensions might be affected by this context change. Subsequently, the analyst can conduct a specified analysis, focusing exactly on the time period and level of abstraction that is relevant for the respective context change to uncover cues, iterating back and forth until enough information is obtained. When pursuing this usage path, an analyst's approach can be guided by questions such as 'What data on contextual changes is available in the organization?', 'Did any relevant changes occur to the process itself (process-immediate context), within the organization (organization-internal context), or outside the organization's boundaries (organization-external context) during the time of analysis?', 'How could these context changes affect the business process?', or 'How might these context changes be reflected in different process mining results?'.

Both usage paths essentially revolve around an iterative process of going back and forth between process mining analysis and contextual analysis until enough information is obtained to be able to make confident decisions. To achieve this common objective, our taxonomy plays two central roles. First, it helps to avoid that the search for more information is stopped too early. Second, it gives confidence to process analysts when they eventually decide to stop their search. Figure 6 below summarizes both paths and displays the iterative nature of the taxonomy application. Importantly, these two usage paths depict broad scenarios. There can be more specific, even hybrid ways of using the taxonomy.

8 Implications for Research

8.1 Managerial and Organizational Implications: The Role of Context

In line with the increasing interest around managerial and organizational implications of process mining [1–5], this paper foregrounds the role of context. Our work is motivated by the observation that process mining results are not self-explanatory. While they show *what* is happening regarding dynamics and changes in a given business process, they do not explain *why* these dynamics occur. Context, to this end, is essential for sense-making of process mining results because it specifies the reasons and factors underlying dynamic process changes. Against this background, our paper contributes to managerial and organizational implications of process mining in three ways.

First, our paper organizes context into specific levels and dimensions that are involved in the dynamic changes of business processes. We systematically integrate existing efforts dealing with context in and around business processes [17, 28, 30] with empirical findings from routine dynamics [13, 43, 44]. As a result, our taxonomy particularly emphasizes contextual factors that are crucial for explaining dynamics in process mining results. Importantly, process dynamics do not unfold in a uniform way; they can vary based on the temporality of change. Broadly, process dynamics can be categorized as either continuous, where change occurs gradually over time, or punctuated, characterized by sudden shifts [6, 76]. Certain dimensions of our taxonomy align more closely with one type than the other. For instance, activity-related aspects are often linked to continuous change, as they evolve incrementally through adaptations in tasks and workflows. In contrast, dimensions such as regulations, policies, and laws tend to drive punctuated changes, as they introduce abrupt and significant shifts in the process landscape. As a result, context is a broad term that can refer to all kinds of cues and features of a given situation. This also poses a problem: When many things are potentially relevant, how can analysts select those that are actually useful? Previous research around process mining seems to have implicitly assumed that analysts simply know where they should direct their attention. Similarly to business process redesign, where most techniques have been found to follow the "ATAMO-principle" ('And then a miracle occurs') [77], many of the crucial steps in sense-making were left to the analyst's discretion. To this end, our context taxonomy not only offers a means to map context, but it also helps analysts to systematically scan, evaluate, explore, and integrate context in process mining projects.

Second, our paper specifies scenarios suggesting how the context taxonomy can be used in practice. Importantly, our taxonomy will not lead to immediate insights. Rather, it enables triangulation and guides further investigation and data collection to inform or validate assumptions [75]. To this end, we have also outlined usage pathways to explain how and why the taxonomy can be used. In some cases, analysts recognize results in process mining analyses that warrant further exploration; here, the context taxonomy informs them about potential context dimensions and levels they might consider. In other cases, analysts know that certain contextual changes have occurred which can have an effect on business process dynamics; here, the context taxonomy helps analysts to specify and narrow down relevant contextual factors to subsequently investigate process mining results. In both cases, the context taxonomy helps process analysts to make informed decisions and derive meaningful actions [25].

Third, from a research point of view, our paper contributes to the ongoing debate around the connection of BPM and routine dynamics research [10, 12, 78]. The observation here is that organizational routines and business processes refer to the same phenomenon, but are studied by two research communities with different assumptions and interests in mind [12]. So far, researchers were mainly interested in integrating knowledge from the BPM field into the routine dynamics community, for instance, by using process mining tools for theorizing [6, 10]. This paper is the first to explore the connection between these two fields the other way around. By using empirical and theoretical insights from routine dynamics research, it specifies how analysts can accomplish sense-making when they face process mining results. Future research can further unpack the role that routine dynamics research can play for BPM, for instance, by integrating qualitative-inductive research methods into business process-related research projects.

8.2 Context-Oriented Process Mining

The ideas and findings of our work highlight the importance of several research directions for engineering-based research in process mining, emphasizing the need for a more prominent role of the detection and visualization of changes and their context:

First, we recognize that contextual changes, particularly within process-immediate and organization-internal contexts, can often be detected automatically with computational techniques. For process-immediate context, this could involve identifying changes in activity and resource-related aspects, while for organization-internal context, it could encompass shifts in roles and social learning. Detecting changes at these levels can significantly enhance the efficiency and adaptability of systems, potentially automating parts of the usage paths outlined in Figure 6. Existing works in process mining, such as the identification of changes in resource behavior [79] and general concept drift detection, already contribute to this direction. However, much of the current research focuses on detecting the occurrence of concept drifts (i.e., identifying when they happened) [39, 80] and comparatively little attention has been paid to characterizing these drifts (i.e., understanding how processes have changed) [81]. Here, a key opportunity for advancing concept drift detection lies in the integration of contextual information, which could enhance the automated characterization of process changes and, in turn, enable meaningful sense-making. Advancements for this and related tasks could be achieved through the incorporation of techniques for explainable AI, such as SHAP [82] and LIME [83], which have so far—in process mining—primarily been applied for predictive process monitoring [84].

Furthermore, existing process mining techniques could evolve by incorporating a broader range of data sources beyond event logs to provide a richer understanding of contextual shifts. Large language models and agentic systems present promising avenues in this regard, as they can process and synthesize unstructured data such as, for example, source code repositories related to IT changes (process-immediate), organizational hierarchies (organization-internal), or regulatory documentation (organization-external) [85, 86]. By leveraging such heterogeneous sources (and their change over time), these systems could add contextual information and enable more nuanced sense-making of process mining results. Importantly, however, this approach also raises critical questions: What types of data are necessary to support these techniques, and does such data exist in practice? Addressing these challenges will be crucial for developing more robust and context-aware process mining techniques.

Second, although some forms of context change can be directly detected in event data, others may only be inferred through their observable impact on a process. For example, complexity measures might be leveraged to uncover process changes over time to subsequently investigate associated contextual changes [11], as illustrated in Figure 4. Gaining clear insights into these occurrences offers a powerful foundation for the insights-driven usage path outlined in Section 7. This highlights the need for developing tailored visualization techniques that can effectively reveal these dynamics, such as illustrating how the control-flow of a process evolves over time by accentuating changes in a directly-follows graph. Addressing this need aligns with a broader trend in recent process mining research, which increasingly emphasizes advanced visualization approaches, often in collaboration with the visualization research community through joint events and initiatives [87].

8.3 Limitations and Further Research

By enriching process mining results with context-based sense-making, we showed how we can obtain an in-depth understanding of what was happening in and around business processes. Our illustrative case depicts scenarios where dynamics and changes in process mining results can be related to one specific explanation. In other cases, analysts may find that more than one aspect of the taxonomy can apply and that contextual factors might be interrelated. For example, regulation-related changes at the organization-external level could be linked to intra-organizational dynamics in the organization-internal level. Similarly, there can be cross-case influences when the performance of one process affects another, such as when they share the same resources [88]. Such scenarios should be explored in future research.

Further research can also study if, and to what extent, our context levels and dimensions can be detected through computational means [7]. In other words, whereas we locate sense-making on the side of process analysts, it might be further "outsourced" to computational techniques. Finally, it is interesting to see how our taxonomy is used during sense-making. Using thinking-aloud protocols, for instance, can shed light on the specific questions analysts ask as they interpret process mining results.

9 Conclusion

Context is essential for interpreting process mining results, as it explains the underlying dynamics and changes in business processes. In this paper, we developed a Process Mining Context Taxonomy that integrates insights from BPM, routine dynamics, and process mining research. This taxonomy comprises three levels—process-immediate, organization-internal, and organization-external—each with dimensions critical for sense-making. Its applicability was demonstrated through a real-world case and evaluated by 20 process mining experts. To facilitate its practical use, we outlined two usage paths for applying the taxonomy in process analyses.

Our research is among the first to systematically structure context for interpreting process mining results, contributing to the broader discourse on the managerial and organizational implications of process mining. By establishing a foundation for examining context in process mining, we open up avenues for future research, particularly in developing computational approaches for automated context detection and integration into process mining analyses. While promising, these advancements will require balancing automated insights with the nuanced understanding that only domain expertise can provide.

Statements and Declarations

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Data availability. The supplementary materials for the current study can be accessed here: https://tinyurl.com/2a6kffru

Ethics statements. Consent to participate: Participation in our user study was entirely voluntary. Participants could withdraw at any time without providing a reason. All identifying information was anonymized during data collection. Consent to publish: The intent of publishing the study's findings was made transparent by mentioning the connection to the research project and the research team at the beginning of the user study. Participants could opt out at any stage, in which case their data was excluded from analysis and not used further.

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