A Context Framework for Sense-making of Process Mining Results

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***Abstract*—Process mining research has made tremendous progress in analyzing, visualizing, and predicting the performance of business processes through computational techniques. However, little attention has been brought to understanding why and how business processes behave as they do. Process mining results alone are not sufficient to arrive at meaningful interpretations about the dynamics and changes of a given business process. Rather, we need to account for contextual factors that underlie and explain the behavior of processes. In this paper, we make two central contributions. First, we develop a framework that depicts relevant factors to make sense of process mining results. The framework is intended to help researchers and practitioners explain why and how processes change across a variety of contexts. Second, we demonstrate the application of our framework within a real-world case: a customer onboarding process in a European financial institution.**

***Index Terms*—process mining, sense-making, context, process dynamics, process change, routine dynamics**

I. Introduction

Process mining research focuses on the development and refinement of algorithms to visualize, analyze, and predict the performances of business processes. The use of process mining impacts organizations in various ways [1], and recent works stress that more focus should be placed on the managerial implications and how it is actually used in organizational practice [2]–[6]. One aspect that has received little attention is the role of context in interpreting process mining results [7], [8]. The observation here is that results obtained through process mining alone (e.g., based on visualizations) are not self-explanatory; they are the result of situational circumstances, which, in turn, explain why and how a given business process is subject to dynamics and change [7].

Consider, for instance, a process analyst looking at process mining-based visualizations of a business process for the first time. Process mining results indicate a high level of variation in the process. This, however, can be the case for a variety of reasons. On the one hand, variations can result from a process running inefficiently [9]. On the other hand, it may be the case that variation is desirable in a setting that requires ongoing adjustments to changing environments [10]. As an example, consider the study by Pentland et al. [10] who use process mining to analyze a patient check-in process in a hospital. They find abnormal changes in the performance of the process over time, which may typically be seen as undesirable because they hamper efficiency and effectiveness. Through contextual analyses, the authors find that the observed dynamics reflect flu season-related adjustments of medical staff. They are desirable and positive for the hospital staff. Hence, process analysts need to understand process dynamics so that they can determine what is going on and how to find actionable improvement opportunities. In short, contextual factors are key for the analyst to understand process behavior and decide on relevant actions.

But what are contextual explanations for dynamics and change in business processes? And how do we obtain such knowledge? These questions have been addressed by a different research community, namely in the field of organization sciences. More specifically, *routine dynamics* researchers have built detailed and multifaceted explanations about dynamics and change in processes. These are typically based on inductive research designs, involving ethnographies and interviews. Importantly, what these researchers understand by “routines” corresponds to what Business Process Management (BPM) researchers understand by “business processes” [7], [11]. Hence, findings from routine dynamics research can help process analysts to better understand the factors that are involved and give rise to dynamics and changes observed in process mining results. [10], [12]–[14].

Against this backdrop, the goal of this paper is to develop a framework for context-based sense-making of process mining results. To this end, we fold two research streams that are concerned with dynamics and change in business processes: we integrate approaches from BPM and process mining with research on routine dynamics. Our framework makes two central contributions. First, we show how relevant contextual factors can occur at different levels. Reviewing empirical findings from routine dynamics research, and integrating them with established context frameworks from the BPM field [15], [16], we organize context around the (1) process-immediate, (2) organization-internal, and (3) organization-external levels. For each level, we provide a number of sub-dimensions.

Second, we demonstrate the application of our framework on the grounds of a real-world case: a financial institution in Europe. Here, we show how the integration of context can enable and inform sense-making of process mining to understand why and how a process dynamically changes. We specify how practitioners and researchers can use our framework.

II. Background

A. 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 [17], [18]. 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 [4]. 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 in organizations [2]–[6], [19]. 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 [2], [20]. Nonetheless, process mining results are by no means self-explanatory. For example, when process mining reveals a given business process is performed in a variety of ways, there can be a number of different explanations for this variation [7], [10]. Hence, one should consider the conditions and circumstances in which a process is performed, i.e., their *context*.

B. 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" [21]. Context has been considered in BPM research to stress how business processes are embedded in environments that impose certain requirements [15], [22]–[25]. Along these lines, the focus on context is considered to counter the "one-size-fits-all approach" that had been traditionally applied in BPM [16]. 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 [26], how context can be captured to improve predictions made about ongoing process instances [8], [27] as well as to improve other process mining techniques [28], [29], or how it can be considered in the visualization of control-flow behavior [30], [31]. Overall, however, contextual explanations have neither been in 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 [24] suggest how process mining techniques can consider context by mining additional context types, including *instance context*, *process context*, *social context*, and *external context* [24]. 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 modelling and design, Rosemann et al. [15] 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. [22] 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.

C. 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 [7], [14]. Studies on *routine dynamics* seek to understand *why* and *how* processes dynamically change over time [7], [10], [32]. Crucially, while these studies speak about *routines* as their focal phenomenon, they refer to business processes [7], [10], [11]. 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], [11].

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 [33], 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 [34]; or to show that processes are performed differently whenever certain stakeholders, such as higher-status managers, are involved [35]. 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.

III. Methodological Procedure and Conceptualization

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 [11]. In conceptualizing our framework, we pursued the following questions:

- What kinds of changes and dynamics can occur in business processes?
- How can they be explained?
- To what extent can we generalize these explanations as contextual factors?

To answer these questions, our approach followed two main steps: (1) We synthesized research from BPM and routine dynamics to develop an initial understanding of context levels and dimensions and conceptualize an initial framework. (2) We systematically reviewed and coded articles on routine dynamics to validate and refine our context framework in light of a broader range of empirical studies of process dynamics. We describe both steps in detail below.

A. Step 1: Synthesis and Conceptual Integration of Context Dimensions

In the first step, our goal was to develop an initial framework for making sense of process mining results, including broad context levels and more specific dimensions.

We adopted the principles of a narrative review methodology [36]. 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 [11]. Hence, we based the development of our framework on phenomenon-driven theorizing [36]. 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 and 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 [15], [22]–[25]. As argued in Section II-B, 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], [14], [34], [35]. In an iterative process, we discussed which context dimensions may broadly affect process dynamics, and vice versa, 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 [15], [22], [24]. Since previous findings in BPM research and routine dynamics research have shown that this dimension can be crucial to explain process dynamics over time [26], [34], we kept this dimension in our framework. 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. [15].

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

B. Step 2: Systematic Review and Coding of Empirical Studies on Routine Dynamics

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 framework'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. [37]. 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 do not relate to routine dynamics at all. This led to a set of 52 remaining articles. Additional forward and backward searches led to an additional 13 articles. In total, we identified 65 articles.

Subsequently, we systematically coded all articles using the dimensions from the initial framework 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 step 1 to sensitize us towards contextual explanations. On the other hand, we remained open to results that could not be subsumed by our initial framework; 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 [8], [38]–[40].

Over the course of this step, we refined several context dimensions of the framework. For instance, the initial framework 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 sub-dimension to "identity-related aspects" to include a broader array of contextual explanations, including those related to strategy and culture [41]; 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 here: https://tinyurl.com/yhc3u8fy

IV. Framework for Sense-making of Process Mining Results: Context Levels and Dimensions

Our framework consists of three context levels: *process-immediate*, *organization-internal*, and *organization-external*. Each level comprises 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. These include sources more related to social dynamics (such as learning dynamics or policy changes). In contrast, others can be associated with technical problems (such as changes in data standards). The framework is depicted in Table I. 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 [32], [49]. We adopt this category from existing frameworks [15], [16] 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 [43]. Also, some activities might become less relevant and occur less frequently over time without any intentional intervention [42].

Resource-related aspects refer to resources involved in the process, such as process participants or information technology. Availabilities [50] and workarounds [51] 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 [34]. Resources may be more or less available at a given point in time, prompting process participants to find ad-hoc workarounds and temporary deviations [38].

IT system features refer to the fact that almost all work-related activities are performed with or through IT systems. Since the functionalities of such systems can change [52], this dimension considers corresponding dynamics in business processes. These can occur, for instance, when IT systems introduce new features that restrict traditional work practices [12]. Technical problems, such as when new features in an IT system do not work properly, can create backlog and lead to dynamics in the process [44].

Organization-internal context. This context level refers to factors that occur inside the 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 [45] or leadership styles [35] can impact the ways processes are being carried out. This level is based on integrating existing context levels, such as the *internal layer* in [15] and the *organization dimension* in [16]. We specify three 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 [45]. 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 [46].

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 [45]. Dynamics can also be caused by changes in resource assignments [39].

Identity-related aspects refer to values and shared understandings, and associated conventions and practices that are specific to a given organization [53]. For instance, an organization may have distinct internal guidelines on how certain cases should be handled and prioritized [35], [54]. Identity-related aspects can also be reflected in (e.g., self-developed) IT-infrastructures that necessitate specific process behavior [55].

Organization-external context. This context level refers to contextual factors that lie outside the boundary of the organi-

TABLE I
A FRAMEWORK FOR SENSE-MAKING OF PROCESS MINING RESULTS

Level	Dimension	Description	Examples
Process-immediate context	Activity-related aspects	Changes in the sequence of activities and events	• Activities are removed, added or changed [32], [42] • Participants learn and forget [43]
	Resource-related aspects	Changes in the availability of resources	• Process participants are absent, prompting improvisation [34] • Resources are unavailable, leading to workarounds [38]
	IT system features	Changes and issues in IT systems	• New features disrupt established work processes [12] • Technical problems lead to backlog [44]
Organization-internal context	Intra-organizational dynamics	Dynamics within organizational boundaries	• Social learning in a group [45] [34] • Process improvement initiatives [46]
	Structural and procedural aspects	Changes in the organizational set-up	• Changes in roles [45] • Changes in resource assignments [39]
	Identity-related aspects	Shared understandings and related practices	• Specific approaches for case handling [35] • Self-developed IT infrastructure
Organization-external context	Environmental dynamics	Changes in the environment	• Covid-based disruptions [47] • Seasonal changes [38]
	Inter-organizational relations	Relations between organizations	• Changes in coordination patterns [48] • Resource delays
	Regulations, policies, and laws	Guidelines affecting business processes	• Privacy regulations affect data processing [40] • Compliance rules change process flexibility [15]

zation but can still have a direct impact on how a business process is performed. This dimension 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 [16] and the *external layer* from [15]. The following three dimensions are relevant for sense-making of process mining results.

Environmental dynamics can have a direct impact on business processes when they cannot be performed in the way they were usually performed. For instance, changes in demands during the Covid-19 pandemic made specific processes outcomes more or less desired [47]. Also, seasonal fluctuations can lead to changes in resource availabilities, which, in turn, can change the performance of business processes [38].

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) [48], leading to irregularities in timing. Delays in resources can, in turn, cause delays to certain process executions [56].

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 [40]. Also, new compliance regulations can enable or restrict the flexibility of a business process [15]

V. DEMONSTRATION OF THE FRAMEWORK

To demonstrate our framework, we draw from real-world data from an 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 dynamics. Hence, the following examples should showcase how our framework 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 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 a variety of event log data. 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 [32], [57], which estimates the total number of ways through which a process can be performed from source to sink at a given point in time. Complexity is a common measure to compute variations in a business process [58]. When analyzing this measure for the onboarding process over two years, we find that the complexity of the process dynamically changes over time. For instance, as depicted in Figure 1, 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

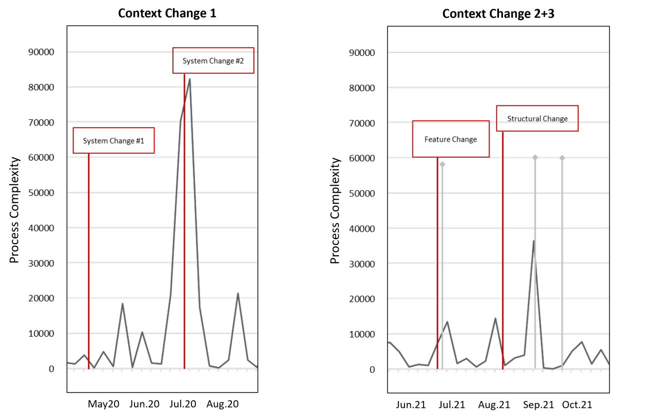

Fig. 1. Snippets of process mining results of the onboarding process to illustrate the context framework

paper: Process mining results alone are not sufficient to explain *why* and *how* a process changes over time. The dynamics in the 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 framework, we systematically enrich the process mining results with context-based sense-making. We demonstrate this in three examples. Figure 1 depicts selected snippets of the complexity changes. 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 framework: process-immediate (IT system functionality), organization-internal (structural aspects), and organization-external (inter-organizational relations) contextual changes within the onboarding process.

Illustration 1: Process-immediate Level/IT System Features: The first contextual change we illustrate refers to the IT system. This is depicted on the left side of Figure 1.

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 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 was 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*.

Illustration 2: Organization-internal Level/Structural and Procedural Aspects: The second contextual change we present is depicted on the right side of Figure 1. 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 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, this complexity decreased as users became more familiar with their new tasks and utilized the provided training programs.

In brief, this illustration reflects how process mining results can be explained through changes at the *organization-internal level* and in terms of *structural and procedural aspects*.

Illustration 3: Organization-external Level/Inter-organizational Relations: Lastly, we describe dynamics visible at the end of June 2021, as visualized on the right side of Figure 1. Analyzing the process complexity, a sudden increase is evident. On a closer look, this was related to an initiative to facilitate process automation. This increase could not be explained at first. It could be clarified, however, through the collection of contextual insights, in particular through interviews with the lead developer as well as analyses 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*.

VI. Implications: Informing Sense-making of Process Mining Results

This paper offers a systematic analysis of contextual factors to make sense of process mining results. Our work is motivated by the observation that process mining results are not self-explanatory. They show *what* is happening regarding dynamics and changes in a given business process. But they do not explain *why* these occur. Along these lines, our work follows recent arguments that more attention should be shifted to managerial aspects of process mining, in addition to the established focus on technical matters [2]–[4], [19]. Against this backdrop, our framework offers a guideline for practitioners and researchers who are concerned with the analysis of process mining results.

The use of the framework is demonstrated through our real-world illustration. When a process analyst is confronted with dynamics but cannot explain how and why these occur, our framework provides an orientation to search for suitable explanations. This is not to say that our framework will lead to immediate insights. Rather, the framework can be seen to enable triangulation by shifting attention to specific sources of dynamics and guiding further interrogation and data collection to inform or validate assumptions. For instance, in the illustrated case, we still needed to talk to relevant stakeholders, such as process participants or managers. Nevertheless, our framework is a useful starting point for analysts to know *what to look for* when confronted with process mining results. Context-driven sense-making, in turn, helps to make informed decisions and actions [19].

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 the process. Our illustrative case depicts scenarios where dynamics and changes in process mining results can be related to one specific explanation. In other cases, the analyst may find that more than one aspects of the framework apply and contextual factors are interrelated (e.g., regulation-related changes at the organization-external level can be linked to intra-organizational dynamics in the organization-internal level). Similarly, there can be a cross-case influence when the performance of one process affects another, such as when they share the same resources [59].

Finally, our work adds to the emerging interest in managerial implications of process mining [2]–[6], [19]. While these works point to various aspects of how process mining causes changes for an organization [2] or how managers adjust their practices [5], we examine how the interpretation of process mining results can be enabled.

Further research can build on our work in two ways. First, it can be studied if and to what extent our context levels and dimensions can be detected through computational means [8]. In other words, whereas we locate sense-making on the side of process analysts, it might be further "outsourced" to computational techniques. Second, it is interesting to see how our framework 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.

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