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The Process Mining Use Case Canvas: A Framework for Developing and Specifying Use Cases

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Abstract

Process mining has emerged as a crucial technology for digitalization, enabling companies to analyze, visualize, and optimize their processes using system data. Despite significant developments in the field over the years, companies—notably small and medium-sized enterprises—are not yet familiar with the discipline, leaving untapped potential for its practical application in the business domain. They often struggle with understanding the potential use cases, associated benefits, and prerequisites for implementing process mining applications. This lack of clarity and concerns about the effort and costs involved hinder the widespread adoption of process mining. To address this gap between process mining theory and real-world business application, we introduce the "Process Mining Use Case Canvas," a novel framework designed to facilitate the structured development and specification of suitable use cases for process mining applications within manufacturing companies. We also connect to established methodologies and models for developing and specifying use cases for business models from related domains targeting data analytics and artificial intelligence projects. The canvas has already been tested and validated through its application in the ProMiConE research project, collaborating with manufacturing companies.

Keywords

Process Mining; Use Case Canvas; Framework; Manufacturing; Order Processing

1. Introduction and Motivation

Today, companies use various information systems (e.g., ERP, SRM, MES, CRM) to manage their business processes efficiently. These systems store vast amounts of data that contain valuable insights into the processes within a company. While traditional business process management approaches focus on qualitative analyses regarding the process as designed, they typically neglect the available process data. On the other hand, data mining techniques cannot capture the complex temporal relationships present in process data. This gap between traditional approaches and data-driven analysis is where process mining emerges as a promising solution.

Process mining is an evolving discipline at the intersection of process and data science. Its data-driven approaches leverage process data to uncover the actual process dynamics, allowing for qualitative and quantitative analyses. Process mining contains three primary subfields [1]: (1) process discovery, exploring process models from process data; (2) conformance checking, identifying deviations in the execution of a process compared to a given process model; and (3) process enhancement, focusing on methods dealing with business process improvement. Recent developments in areas like object-centric process mining, process digitization and automation, and integrating artificial intelligence for predicting process outcomes are helping to address increasingly complex questions. An overview of process mining and its seminal subfields can be found in [1,2].

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The application of process mining in manufacturing companies offers various benefits. For example, it enables identifying and reducing bottlenecks and repetitive tasks like rework by providing a holistic view of processes down to individual activities. It also facilitates the identification of automation opportunities and fosters process standardization by minimizing the number of process variants, ultimately enhancing process efficiency and reducing throughput times. Moreover, process mining supports root cause analysis, e.g., tracing quality issues back to specific process steps in manufacturing. Despite these advantages, the adoption of process mining in manufacturing companies rarely gains traction due to various challenges. Established project methodologies tailored to process mining [5,3,4] structure such projects into distinct phases and guide their implementation. However, the main challenges confront companies already during project initialization. These challenges include uncertainty about project outcomes, selecting adequate processes, defining success metrics, and data availability and privacy concerns [6]. Small and medium enterprises often require additional guidance and expertise to develop and implement process mining use cases effectively, which can be crucial for the success of a process mining project.

To address these challenges and support manufacturing companies, we introduce the *Process Mining Use Case Canvas*, a semi-formal framework describing process mining use cases, facilitating interdisciplinary communication, and structuring complex subjects [7,8]. By encompassing the key components of a process mining use case and providing a structured approach for its specification, the *Process Mining Use Case Canvas* aims to foster a shared understanding between process mining experts and stakeholders within a manufacturing company [10,9].

The remainder of this paper is structured as follows. Section 2 overviews existing process mining project methodologies, established canvas models, and related work on process mining use cases. We present our Process Mining Use Case Canvas in Section 3 and elaborate on its components. The application of the canvas and its limitations are discussed in Section 4 before Section 5 concludes the paper.

2. State of the Art and Related Work

In this section, we highlight the state of the art when developing and specifying process mining use cases and present related work. To do so, we first go into more detail about process mining project methodologies. Then, we evaluate various use case canvases from related fields before discussing tangible approaches to process mining use cases.

2.1 Process Mining Project Methodologies

Several methodologies have been developed to assist and guide companies in implementing and executing process mining projects. The first project methodology specifically for process mining is the *L* life-cycle model* [1,3]. It includes ten process mining related activities (e.g., discover, compare) divided into cartography, auditing, and navigation categories, guiding users through implementing a process mining project in five stages. While four stages address the project execution from extraction to operational support, an initial *Stage 0* emphasizes the project planning and justification. The *Process Mining Manifesto* [3] also provides guiding principles and states potential challenges specific to process mining projects. The *PM² methodology*, proposed by van Eck et al. [4], introduces an iterative project approach and emphasizes interdisciplinary collaboration between process analysts and business experts. It considers six stages among three phases: an initial phase, the analysis iteration loop, and a final phase regarding improving the process and supporting operations. The first stage *Planning* involves selecting business processes, identifying research questions, and composing a project team. For each of these activities, they highlight its relevance and potential challenges (e.g., data quality or unclear research questions). Aguirre et al. [5] offer a step-by-step methodology with four stages for conducting process mining projects. The initial project definition stage involves defining the main process problems, specifying the scope, modeling the process, and setting the project goals. The second stage handles data localization, extraction, and preparation. The conducted case studies reveal main challenges such as data quality problems, privacy concerns, unclear success measures, or difficulties regarding data extraction.

Although the discussed methodologies guide the execution and structuring of process mining projects, their support to systematically develop and specify appropriate use cases is limited. The use cases have to be developed and specified beforehand or at the beginning and require more comprehensive design aspects beyond the processual description by the methodologies.

2.2 Approaches Regarding Canvas Models

The Business Model Canvas by Osterwalder and Pigneur [9] is probably the best-known canvas model used for structuring and communicating business models. It has inspired numerous canvases and is helpful for practitioners to visualize and analyze business models. Some aspects of the Business Model Canvas can be adapted for developing process mining use cases. However, there are limitations in using this canvas for process mining use cases, as it does not consider the process view and analytical aspects.

Some authors propose data-centric approaches, including canvases for data-driven use cases or data science. For instance, Kronsbein and Mueller suggest a Data Innovation Board [11], offering a solution for generating initial data-centric ideas. Kayser et al. present a data classification scheme for data-driven use case development [12]. Schwarz et al. propose a canvas for data and analytics use cases, with some aspects applicable to process mining, including value creation, data availability, roles, and tools [13]. Neifer et al. introduce the Data Science Canvas [14], which partially applies to process mining use cases. However, further process mining specific components like process-related components or more precise guidance regarding the process mining analyses would be needed. While all these canvases offer valuable input, they are only partially applicable for process mining use cases as they focus solely on data and neither guide further use case development nor focus on processes and process mining specific aspects.

Other approaches specifically focus on technologies like machine learning (ML) and artificial intelligence (AI). Bork et al. [15] highlight integrating ML solutions into the business context and discuss the data-driven and canvas-driven approach. The authors conclude that most of the analyzed canvas-driven approaches focus on data and technology but only a few on business or process dimensions. Thiée's systematic literature research [8] provides a comprehensive overview of existing canvases for machine learning. Kerzel's AI canvas [16] has a more generic focus on AI and comprises a business view and a model & data view. It explores how AI use cases can impact the organization and create business value. Additionally, Steireif et al. [17] propose a participatory approach for identifying, specifying, and evaluating AI use cases in manufacturing, introducing criteria related to technology attractiveness and implementation capability. While some technical and organizational criteria from these four approaches may be transferable, they cannot fully capture process mining use cases. The analyzed canvases often do not consider processes, which makes it necessary to adapt and extend the components.

The previously described approaches show that although they already contain components helpful in designing use case aspects, they cannot provide a comprehensive approach for systematically developing and specifying process mining use cases. Nonetheless, we can adapt and include some existing components in developing such a model.

2.3 Approaches Regarding Process Mining Use Cases

Ailenei et al. [18] focus on defining and validating specific process mining use cases. A literature review, ten interviews, and a survey result in a list of use cases categorized by the used process mining technique. For instance, the discovery category contains a use case to determine the structure of an unknown process. Although the development of the use cases remains unclear, and the small number of interviews suggests a limited representation of possible process mining use cases in companies, the article provides valuable inspiration for potential applications of process mining.

As the number of process mining projects increases, vendors develop and implement a wide variety of use cases. For instance, the market leader Celonis describes over 20 selected use cases covering finance, shop floor, strategic applications, and more areas [19]. While this selection can guide companies, they should consider a potential selection bias, as vendors may prioritize certain use cases based on customer preferences or industries. Therefore, manufacturing companies might prefer a neutral method for developing use cases, bringing out use cases that have received less attention.

Rott and Böhm [20] present criteria that guide organizations in evaluating process mining use cases. These criteria, categorized into six groups, focus on business importance, challenges, employee skills, data state, organizational support, and optimization potential. Their relevance, however, is not limited to evaluating a process mining use case; instead, its development should already account for them. Thus, a canvas to comprehensively develop and specify process mining use cases requires additional components reflecting overall goals, reasons for selecting process mining, a process description, and the type of analysis needed.

3. Process Mining Use Case Canvas

The presented canvases offer a foundation for data-based use cases but require adaptions to address the specific challenges related to process mining. Therefore, we derive a use case canvas specifically targeted to process mining projects. But first, we tackle the challenges that have been raised. Most canvases are not designed for the application to processes, which the study in [15] also confirms. In process mining, the process perspective is essential and should be included in a corresponding canvas. As illustrated and discussed in [6], the main challenges of a process mining project already arise within the initialization. The study participants name the benefits of process mining, selection of appropriate business processes, definition of success metrics, and data availability as their primary concerns. The results from [21] support this point of view and identify a lack of process mining expertise and limited understanding of data usage as additional challenges.

Within the ProMiConE research project, we conducted several interviews and workshops with small and medium-sized manufacturing enterprises, confirming the findings of the studies above. Participants emphasize that estimating the effort and outcome of a process mining project, uncertainties about data availability, and data quality problems are significant challenges. Furthermore, many users feel the need to be more sufficiently informed on the opportunities of process mining and thus have difficulties assessing the potential of this technology.

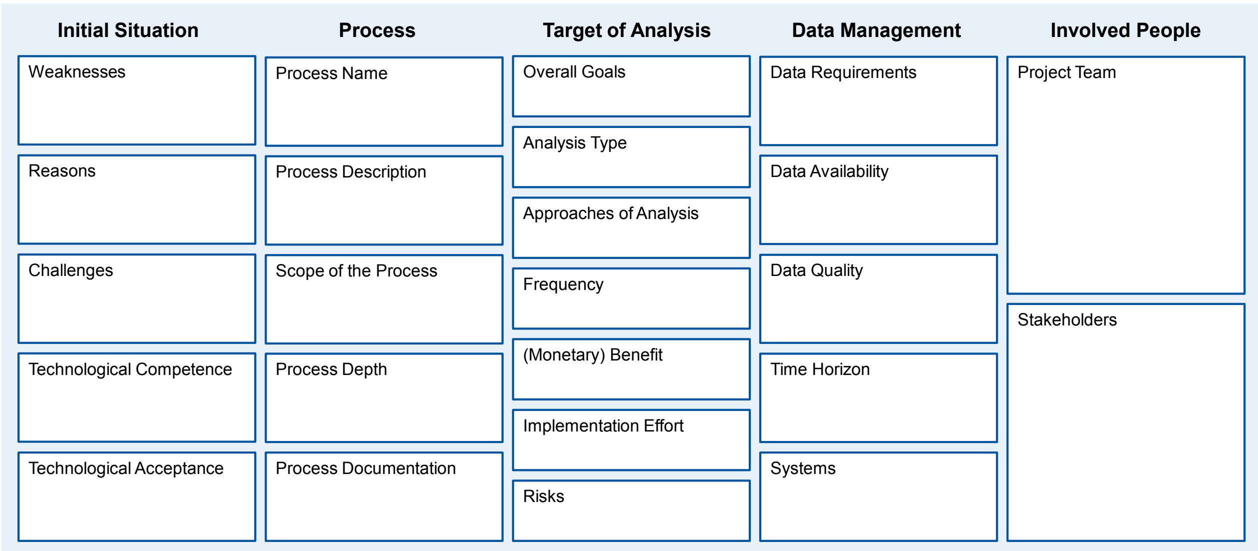

Figure 1: Process Mining Use Case Canvas

The *Process Mining Use Case Canvas* addresses these challenges and enables to identify, develop, and specify process mining use cases in manufacturing companies. It aims to guide and improve the collaboration between process mining experts and company representatives. Each canvas component encourages them to reflect on the specifics of the use case at hand. The associated components are described and defined along the five dimensions: *Initial Situation*, *Process*, *Target of Analysis*, *Data Management*, and *Involved People* (see Figure 1). While existing canvases already address some of the dimensions, their specific application to process mining is novel.

3.1 Initial Situation

In order to assess the company's initial situation, the *Weaknesses* component, in existing canvases [14,20,13] mostly referred to as problems, is intended to describe the current problems and weaknesses that are supposed to be ultimately improved or resolved by the application of process mining. Exemplary weaknesses are a lack of adherence to production schedules or too many process variants. While other approaches aim to choose the right technology [15,14,13,8], we assume process mining to be the methodology of choice. Thus, the *Reasons* component documents the rationale for applying process mining to remedy weaknesses. For example, the ability of process mining to increase process transparency and thus make analysis possible in the first place is a possible reason for its application. Current obstacles preventing optimization measures are described in the *Challenges* component. As mentioned in [20], this includes describing why it has not yet been possible to eliminate the identified weaknesses, for example because of a lack of transparency and various root causes, hence hard to identify without process mining. The *Technological Competence* component considers a company's previous experience and expertise in process mining and other digitalization projects [22,20,17]. For instance, although a company might not yet carry out a process mining project, it can state that it might resort to relevant experience with digitalizing the shop floor. The *Technological Acceptance* component [20,17] assesses the company's workforce acceptance regarding technology and digitalization projects. High acceptance of process mining increases the likelihood that employees will embrace and use the new analytics insights, leading to smoother implementation and greater process optimization success.

3.2 Process

In order to sufficiently capture the process for the use case development, the first step involves documenting the *Process Name* as specified within the company. This identification avoids ambiguity and mitigates the risk of misunderstandings [23]. An example could be the end-to-end manufacturing process. In the *Process Description* component, the process is outlined. A detailed description can additionally indicate which production areas and critical shop floor operations will be included. The component *Scope of the Process* defines the process steps delimiting the process [24]. Exemplary delimiting process steps could be the receipt of a production order as a starting point and the product transport to the packaging area as a final step. The process level at which the respective process takes place and is to be analyzed is defined by the *Process Depth* [25,26], ensuring that the data will have the required granularity. Accordingly, a process can be located, for example, on the level of a main process, a business process, or a work process, whereby the work process can be detailed down to individual activities. The *Process Documentation* component deals with the availability of documentation or description of the process under analysis in the company [5]. Such documentation may be provided in BPMN 2.0 or similar formats and can already give stakeholders an initial understanding of the process.

3.3 Target of Analysis

The *Overall Goals* component, adapted from [5,16], defines the overall goals of the process mining use case to clarify when a process mining project is considered successful. For example, it can be defined that an overall goal is to reduce the process variants in manufacturing. Relevant process mining functionalities are specified in the *Analysis Type* component, as addressed by [5,1,2,4] and consolidated for this canvas. For example, process discovery and bottleneck detection could be mentioned here to identify causes of inefficiencies in manufacturing. Furthermore, the *Approaches of Analysis* component of the analysis records whether the use case is to be classified as descriptive, diagnostic, predictive, or prescriptive. The component is adapted from [22,14,8,2] and consolidated for this canvas. The *Frequency* component defines how often and to which extent the analyses are performed [20,3,27]. The frequency significantly effects the necessary effort and the required data quality. A one-time analysis, periodically repeating application, or a permanent process analysis in real time can be conducted. A repeated analysis, for example, can be necessary to assess and validate improvement measures derived from initial analyses. The *(Monetary) Benefits* component describes the added (monetary) value that can be achieved by the use case [15,12,11,14,9,20,13,17,8]. Such direct and indirect benefits could be eliminated bottlenecks, a measurably reduced throughput time, or an increased service level. Estimating the effort required to implement the process mining use case is focused on in the *Implementation Effort* component adapted from [14,20,13,17,8]. While many sources only address project costs, this component takes a more comprehensive approach, including the necessary staffing, time, and cost efforts. Various risks can accompany process mining projects, e.g., data privacy and compliance risks, insufficient data quality, technical challenges, or resistance to change on the part of employees. If apparent, such project risks are noted in the *Risks* component [11,13].

3.4 Data Management

The *Data Requirements* component, adapted and consolidated from [12,14,20,13], derives the necessary data and its desired target state based on the individual key and driver metrics defined for each goal. Influencing factors are parameters like the type of analysis (pre-facto or post-facto), the desired level of granularity, and the targeted level of significance. In this initial stage, the discussion should solely focus on the desired target state of the analysis and required data. In view of the desired data target state, the component *Data Availability* determines which data is already collected within the company or available from external sources [22,20,13,17,8]. This includes scope, temporal availability of data, existence of raw data for pre-processing, accessibility aspects such as interface availability and compatibility, data security and privacy. In the component *Data Quality*, previously specified available data is now evaluated with regard to their quality [16,14,20,13,8]. In accordance with the defined requirements, the data has to be checked for its completeness, validity, veracity, and consistency. In particular, it has to be verified whether the level of detail in the data suffices the desired level of granularity in the analysis. A characteristic feature of process data is its innate time dimension, which is examined in more detail in the *Time Horizon* component. While the data period or time frame was not explicitly considered in existing canvases so far, we added it as a separate component [28]. The relevant time horizon is estimated based on data volume and frequency. Another distinction concerns whether it is a real-time analysis during operation or a post-facto analysis for long-term investigations to improve the business process. Finally, the *Systems* component describes all information systems involved [22,16,14,20,8]. These include data-providing, data integration and pre-processing systems, as well as data analysis and visualization systems. Here, we distinguish between systems that are already in use and those that have yet to be installed. Also, the primary sources for each data type can be determined and the involved systems' interoperability is evaluated.

3.5 Involved People

The *Project Team* component, adapted and consolidated from [22,11,14,20,13,8], considers roles required in a process mining project, suitable persons to be assigned to these roles and determines whether specific expertise is already available within the company. These roles include the *project manager*, the *process mining expert* and the *data scientist*, all of which can be filled by internal employees or external experts. In addition, the roles of the *process owner*, the *process expert*, and the *system expert* should be filled internally due to the required company-specific in-depth knowledge of the process and information systems involved. People affected by the project should be mentioned in the *Stakeholders* component [15,14,20,13,17,8]. This includes future users of the process mining analyses and those targeted by their measures. In addition, all decision-makers whose areas of responsibility are affected should be considered.

In summary, the *Process Mining Use Case Canvas* structures and supports the development and specification of use cases by assessing the initial situation and deriving the use case based on the identified weaknesses. It characterizes and describes the targeted process in a structured way and enhances understanding of the use case. The actual process mining application is systematically derived from the clearly defined goals through the *Target of Analysis* dimension. In the *Data Management* dimension, the demands on data are brought together with the prevailing situation in the company. Finally, the interdisciplinarity and the implication of a process mining project are considered by addressing the *Involved People*. This way, process mining use cases can be systematically developed and specified based on these five dimensions.

4. Application and Discussion

The *Process Mining Use Case Canvas* has been applied in the ProMiConE research project with two manufacturing companies and validated by an established process mining software vendor. These first two applications suggest that the canvas is suitable for the short-term, initial creation of use cases, starting with idea generation in the company and for the detailed elaboration and specification of use cases. Initial use cases could be formulated by deriving these ideas from the most pressing weaknesses.

We conducted a pilot study using the canvas to develop potential use cases within the ProMiConE project. The two participating companies (see appendix) were selected as the research project focuses on small and medium-sized manufacturing enterprises using ERP systems and are interested in process mining. The companies were informed in advance about the procedure and the canvas so that they had the opportunity to gather the necessary information for the workshops. The workshops took place for each company individually, each with one company representative and a subset of the authors as moderators and experts on process mining, respectively. Initially, the procedure and the canvas, including its components, were explained in detail. Subsequently, the specific components and the respective company's characteristics were discussed. The company representatives provided information on weaknesses, processes, information systems, and other aspects. At the same time, the moderators documented these insights using the canvas and contributed their process mining expertise regarding possible analyses or data requirements. Since the companies had no previous experience with process mining use cases, their goal was first to develop initial use case ideas and describe them. This way, each company developed two or three use cases over the workshops, completing one canvas per use case.

In its first application, the canvas has proven its usefulness. Its current form was well suited to guide and structure the development of use cases in the pilot study and showed no need for adjustments. In addition, we discussed the canvas with a process mining vendor who evaluated its form and content and confirmed its functionality.

These two cases suggest that even when a process mining expert is present, it can be beneficial to educate representatives of manufacturing companies about the possibilities of process mining and different use cases beforehand. Because of the countless ways to apply process mining in manufacturing companies, it takes the internal knowledge of the company representatives involved to identify the most compelling use cases, as the process mining expert does not have sufficient knowledge about the state of the company. The application of the canvas underlines this point, as only the representatives have the knowledge of current weaknesses, which can only be determined with further investigation from the outside. Furthermore, it may be advisable to educate the company representative early on so that there is an opportunity to talk to various stakeholders within the company beforehand to aggregate the information needed to develop the use case. In one case, a company representative followed this approach, and it proved beneficial to the use case development since the person lacked comprehensive information for the use case beforehand.

The application thus far has demonstrated that the canvas should be applied with the assistance of a process mining expert. The expert should guide the user through the canvas, provide important hints and support directly when developing the use cases based on their expertise. It is important to highlight that the canvas only allows a rough estimation of the actual effort required for the process mining project based on the information gathered. As already outlined before, it can be said that at the time of the first use case development there is often uncertainty about the actual data quality [6,21]. For this purpose, after the specification of a use case, a more detailed, use case-specific examination of the data could take place and thus a more precise estimate could be made.

Regarding the challenges discussed at the beginning of this paper in the context of project initialization [6], the pilot study suggests that the canvas supports users in better planning and estimating the expected outcome of the process mining project. Furthermore, the canvas enabled the selection of suitable processes by systematically deriving the process to be analyzed, starting from the company's biggest problems and weaknesses. Even though the canvas does not provide a predefined set of success metrics, it helps users focus on specifying the criteria for project success by providing the corresponding component and facilitating communication with the involved process mining expert. The canvas faces the topic of data availability and privacy by its corresponding component, as well as it considers project risks. Even if the canvas does not describe any use case or process mining project conclusively down to the smallest detail needed for the final implementation, the two applications demonstrated that the structured and structuring character of the canvas fostered exchange, communication, and, above all, reflection about suitable process mining applications in the company. This shows the potential to make process mining applications more accessible and understandable for users. Drawing attention to challenges and possible causes of problems improves awareness, and this early-stage confrontation can mitigate later failures in projects and thus increase the chances of success of process mining in companies.

We intend the *Process Mining Use Case Canvas* as the starting point of any initiative to introduce process mining. Therefore, we designed the canvas to develop or sketch first ideas for potential process mining use cases or to specify them in more depth and detail. In reference to standard process mining project methodologies, the canvas is a suitable complement to be applied at the beginning of a process mining project, or even before, to define the framework and the conditions of a project to be designed and implemented based on the use case.

5. Conclusion and Outlook

The two applications of the *Process Mining Use Case Canvas* suggest that it may bridge the gap for systematically developing process mining use cases and provide a model for potential users to create practice-oriented use cases. With the advancing development of process mining, we intend to adapt and further develop the *Process Mining Use Case Canvas* over time. Since the canvas was only applied with two manufacturing companies and validated with one process mining vendor, it is intended to involve additional partners to broaden the perspective. This is supposed to include small and medium-sized enterprises from other industries and of different sizes. In addition, it has not yet been realized that a use case developed with the canvas is also implemented as a process mining project. It is to be examined to what extent the initially developed use case is modified in the course of a project. Furthermore, since the current focus of the canvas application lies exclusively on manufacturing companies, the canvas is to be transferred and applied to other domains.

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Appendix

Table 1: Description of the participating companies

	Company 1	Company 2
Industry	Plant manufacturing	Metal processing
Manufacturing strategy	Make-to-order	Make-to-order
Size	Medium size company	Small size company
Country	Germany	Germany
Participant	Person with many years of experience in the company in a leading position	Person with many years of experience in the company in a leading position
Number of workshop sessions conducted for use case development	Two	Three
Number of use cases developed	Two	Three
Previous practical experience with process mining	No	No

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