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RESEARCH PAPER

Improving Process Mining Maturity – From Intentions to Actions

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Abstract Process mining is advancing as a powerful tool for revealing valuable insights about process dynamics. Nevertheless, the imperative to employ process mining to enhance process transparency is a prevailing concern for organizations. Despite the widespread desire to integrate process mining as a pivotal catalyst for fostering a more agile and flexible Business Process Management (BPM) environment, many organizations face challenges in achieving widespread implementation and adoption due to deficiencies in various dimensions of process mining readiness. The current Information Systems (IS) knowledge base lacks a comprehensive framework to aid organizations in augmenting their process mining readiness and bridging this intention-action gap. The paper presents a Process Mining Maturity Model (P3M), refined through multiple iterations, which outlines five factors and 23 elements that organizations must address to increase their process mining readiness. The maturity model advances the understanding of how to close the intention-action gap of process mining initiatives in multiple dimensions. Furthermore, insights from a comprehensive analysis of data gathered in eleven qualitative interviews are drawn, elucidating 30 possible actions that organizations can implement to establish a more responsive and dynamic BPM environment by means of process mining.

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1 Introduction

Organizations are subjected to constant change (vom Brocke et al. 2021a), the pace and scale of which are accelerating. There are many reasons for this, which can be broadly classified as exogenous shocks (Röglinger et al. 2022), evolving technology (Baiyere et al. 2020; Kerpedzhiev et al. 2021), and changing customer needs. In response to this ongoing pressure for change, organizations must continuously adapt their organizational structure, which in turn requires professional structures, tools, and capabilities for managing business processes.

Business Process Management (BPM) involves the establishment of a comprehensive set of tools and capabilities to systematically handle the design, analysis, implementation, adoption, and monitoring of business processes (Dumas et al. 2018; Weske 2019; Maris et al. 2023). The foundational concept of BPM posits that business processes can be designed and implemented in a top-down manner (vom Brocke et al. 2014; Rosemann et al. 2008; Recker et al. 2009), often utilizing reference models (Harmon 2010; Houy et al. 2014). It was traditionally believed that processes in organizations only required periodic updates through top-down initiatives after their initial implementation (Dumas et al. 2018).

However, the ever-increasing complexity of our interconnected and digitalized world raises the question of whether traditional assumptions in the BPM discipline have to be revised and improved (Baiyere et al. 2020; Kerpedzhiev et al. 2021; Beverungen et al. 2021).

Simultaneously, emerging digital technologies, while introducing greater complexity and uncertainty in process management, also provide opportunities for more dynamic and flexible responses to change. Examples include the application of artificial intelligence (AI) (Janiesch et al. 2021), robotic process automation (RPA) (Syed et al. 2020), and notably, process mining (PM) (van der Aalst 2016), which has received much attention within the BPM community (Reijers 2021; van der Aalst 2016; Dumas et al. 2018).

Process mining follows a data-driven approach and utilizes data traces of process performances in information systems, such as enterprise resource planning (ERP) systems or dedicated workflow management systems, to analyze the underlying business processes (van der Aalst 2016; IEEE Task Force on Process Mining 2012). In most organizations, data needed for conducting process mining seem readily available (van der Aalst 2016). This potential has led to a surge in interest in process mining in recent years, both in academia and among practitioners (Emamjome et al. 2019; Reinkemeyer 2020). Organizations can benefit from process mining by increasing transparency, identifying deviations, or creating digital representations of their business processes in real-time (Galic and Wolf 2021; van der Aalst and Carmona 2022a; Park and van der Aalst 2021). Additionally, BPM can leverage process mining due to its real-time data processing and analyzing capabilities (van der Aalst 2016; Davenport and Spanyi 2019), which affords live insights on process execution and process drift (Grisold et al. 2020) and allows evidence-based decisions ad hoc. Thus, process mining has substantially improved the flexibility of BPM to manage increasingly greater and more complex process dynamics (Grisold et al. 2022b; Kipping et al. 2022).

However, despite the high expectations surrounding the adoption of process mining, a significant gap often exists between the intention to apply process mining, and the performance of actions resulting in its widespread implementation. Despite the fact that 61% of organizations express the desire to implement process mining or have initiated initial process mining initiatives, widespread adoption remains elusive (Daniels 2022). Even in organizations where process mining is already in use, many still grapple with substantial challenges, such as a lack of management support, issues with data quality, and complex data preparation (Martin et al. 2021). Moreover, research into the value creation of process mining in organizations is a relatively recent undertaking (Badakhshan et al. 2022), and practical guidance for the introduction and establishment of process mining often lacks robust research backing (Reinkemeyer 2020; Linden 2021; Reinkemeyer et al. 2022). This has spurred calls for the development of process mining-related maturity models (Dunzer et al. 2021; Martin et al. 2021) and research into how BPM initiatives can navigate the dynamics introduced by this new technology (Beverungen et al. 2021). Consequently, to overcome this research gap, the design goal of this paper is to develop a maturity model and complementary artifacts to achieve widespread adoption and successful implementation of process mining in organizations.

This paper presents a multi-factor maturity model for assessing and improving the maturity of process mining activities in organizations, comprising five factors with a total of 23 elements, each with five distinct maturity stages. The model was developed using a state-of-the-art research process for creating maturity models (Becker et al. 2009). Additionally, we conducted eleven interviews (Myers and Newman 2007) with practitioners from various domains to identify typical actions organizations can take to improve their process mining readiness across the different factors of the maturity model, thus bridging the intention-action gap. The model can be leveraged by other researchers to theorize on the role of process mining and other data-driven methods and tools in achieving a more flexible and evidence-based approach to BPM. Practitioners, too, can benefit from the maturity model and its application by gaining a comprehensive overview and receiving tangible measures to enhance their process mining readiness, enabling them to manage process dynamics with increased efficiency and effectiveness.

The paper is structured as follows. In Sect. 2, we review the fundamentals of process mining, its relation to process dynamics, BPM, and maturity models. Section 3 outlines the research design. In Sect. 4, we present our maturity model with its respective factors and an application method. In Sect. 5 we describe insights from the interviews outlining actions taken by practitioners to improve organizations' process mining readiness. In Sect. 6, we discuss the implications of our results for theory and practice before concluding the paper in Sect. 7 by summarizing it, pointing out limitations, and providing an outlook on future work.

2 Related Work

2.1 Dynamics in Business Processes

The constant influx and consumer uptake of novel cutting-edge technologies and management concepts requires today's organizations to be increasingly agile, and to be able to adapt quickly to a changing business environment, to new digital technologies, and changing consumer needs (Grisold et al. 2022a). As digital transformation has created more accessible data streams, organizations' information systems have become increasingly intertwined with

their business processes (Pentland et al. 2020). At the same time, increased access to digital trace data has created new opportunities for understanding, describing, and even forecasting the dynamics of business processes (i.e., changes in a process's structure over time) (Pentland et al. 2021; Grisold et al. 2022b). Process dynamics research has its roots in the field of routine dynamics (Grisold et al. 2020). Both business processes and organizational routines provide the theoretical lenses needed to investigate how multiple actors carry out a series of steps that are essential to the execution of work in organizations (Wurm et al. 2021; Dumas et al. 2018).

By breaking down business process dynamics, one central question that research has to answer is whether earlier BPM logics (i.e., process, infrastructure, and agential logics) remain applicable in the context of digital transformation both for practical advice and for BPM theory (Baiyere et al. 2020). In recent years, BPM has proven to be a viable tool for controlling and managing business processes (Dumas et al. 2018; Maris et al. 2023). Nevertheless, the fundamental premise of earlier logics is based on the values and assumptions that have underpinned the improvements in the efficiency and quality of business processes in a largely stable environment (vom Brocke et al. 2014; Rosemann et al. 2008; Recker et al. 2009). However, digital transformation creates an environment that questions how genuine these presumptions are, as BPM logics are unable to account for the dynamics of change (Baiyere et al. 2020). These challenges strongly point to a growing level of complexity connected with BPM, at a time when processes have to be implemented more quickly and more frequently (Beverungen et al. 2021). This requires BPM research to balance the tension between the need to maintain stable, robust and reliable business processes, and the drive to innovate and change processes and routines (Grisold et al. 2022b; Beverungen et al. 2021).

Emerging new technologies, such as AI (Janiesch et al. 2021), RPA (Syed et al. 2020), and especially process mining (van der Aalst 2016) afford increasingly more flexible and detailed insights into process dynamics (Leonardi and Treem 2020). Due to the impact of these new technologies on BPM dynamics (Grisold et al. 2022a), BPM scholarship has become more interested in the dynamics of business processes, aimed at understanding how and why processes develop while they are being executed (Grisold et al. 2022b). Thus, there exists a drive for the development of new capability areas and the adaption of existing frameworks (Kerpedzhiev et al. 2021). Future BPM research should therefore determine whether and how existing BPM assumptions can be changed or combined in order to address the paradox of managing processes at increasingly greater speed and complexity. Ultimately, only organizations that manage to successfully develop transparent and quickly adaptable processes will remain competitive (Beverungen et al. 2021).

2.2 Handling Process Dynamics with Process Mining

Process mining is an interdisciplinary approach that originates in the fields of data science and process science. The goal of process mining is to use event data to extract process-related information to answer questions about processes, and to discover the interactions between the people involved in the process (IEEE Task Force on Process Mining 2012; van der Aalst 2016). This creates the opportunity for organizations to look at real-world processes, instead of assumed ones (van der Aalst 2016). Therefore, the application of process mining requires the execution of a business process with the help of information systems. This generates trace data which can be transformed into event logs, to store process-related information and reflect on the sequence of activities being performed. Using process discovery, this allows to automatically generate as-is process models to enable a better view of how a process unfolds in reality (IEEE Task Force on Process Mining 2012; van der Aalst 2016; Dumas et al. 2018). Aiming to identify and analyze deviations can be achieved by applying conformance checking, whereby an existing process model is compared to an event log of the same process. Moreover, the quality of process models can be improved through the extension and enhancement of existing process models (IEEE Task Force on Process Mining 2012; Marquez-Chamorro et al. 2018; Weinzierl et al. 2020). Additional process mining techniques established in recent years enable the comparison, prediction, and prescription of business processes (Marquez-Chamorro et al. 2018; Weinzierl et al. 2020; van der Aalst 2022).

Process mining is advancing as a powerful tool that can reveal valuable insights into how processes in organizations are performed (Grisold et al. 2020; Wurm et al. 2021; Kipping et al. 2022) and how they change over time (i.e., discovering process dynamics) (Pentland et al. 2021; Wurm et al. 2021). As process mining uncovers human actions using digital trace data it can also shed light on the dynamics of organizational routines (Wurm et al. 2021), which helps coping with the latter's diversity (Breuker and Matzner 2014). This works because digital technologies are becoming increasingly intertwined with work practices and incorporated into organizational routines. As a result, it can indicate how processes evolve and shift over time (Grisold et al. 2020). New evolving self-learning approaches (i.e., predictive and prescriptive process mining approaches) have begun to outperform traditional ones (van der Aalst 2016; van der Aalst and Carmona 2022a), opening doors to an even more dynamic handling of future events (Heinrich

et al. 2021) or concept drift (Sato et al. 2021). These methods and techniques enable organizations to analyze their processes quickly and comprehensively, both in an offline and an operational context, enabling a more dynamic handling (Grisold et al. 2020). Using these process mining techniques, event data can be examined from various angles and "critical events" that indicate change can be identified (Grisold et al. 2020). While there are numerous ways of theorizing from process data (Langley 1999), it is vital to identify these critical events as they characterize patterns of change dynamics and show how multiple temporalities, degrees of analysis, and contextual elements interact to create a phenomenon (Grisold et al. 2020). As this adoption of process mining can cause unanticipated dynamics in organizations, insights from routine dynamics research can and should be used for explanation (Grisold et al. 2021; Berente et al. 2016). Nevertheless, to fully understand the dynamics of change, digital trace data has to be contextualized with additional data (Grisold et al. 2020). Thus, using process mining enables organizations to cope with the ever-increasing dynamics in today's processes (Grisold et al. 2020; Pentland et al. 2021; Wurm et al. 2021; Kipping et al. 2022) and to create business value (Badakhshan et al. 2022).

One way of managing processes more dynamically in organizations can be achieved by the means of process mining. Several papers have examined the managerial perspective of process mining (vom Brocke et al. 2021b; Eggers et al. 2021; Grisold et al. 2021; Martin et al. 2021). In order to learn more about the perceived advantages and challenges of implementing process mining in organizations, four key areas of management-level are of great interest: effort and cost-benefit analysis, organizational implications, leadership and governance implications, and data accessibility and privacy concerns (Grisold et al. 2021). To further achieve a more mature adoption of process mining, success factors have been proposed in the literature, namely, project management, management support, structured process mining approach, data and event log quality, resource availability, and process miner expertise (Mans et al. 2013). These success factors have been reviewed and three additional ones, namely, change management, tool capabilities, and training, have been identified (Mamudu et al. 2022). Additionally, the factors management support, resource availability, and process mining expertise were adapted and restructured, resulting in three new factors such as stakeholder support and involvement, information availability, and technical expertise (Mamudu et al. 2022). This suggests that successful process mining projects require a diverse set of competencies in the field of organizational structures, data and information prerequisites, and knowledge about tools and process mining (Mans et al. 2013; Mamudu et al. 2022). Organizational structures and governance are perceived to be important factors and to play a guiding role when implementing process mining (Badakhshan et al. 2022). Additionally, in practice, process mining often requires different business units like information technology (IT), BPM, or a relevant business department, to collaborate with each other (van Eck et al. 2015). Consequently, most organizations follow a project-based approach to conduct process mining (Reinkemeyer 2020; van Eck et al. 2015). After prolonged application, a dedicated department is beneficial to accelerate the adoption of process mining, and to concentrate the necessary resources (Reinkemeyer et al. 2022).

Hence, the consequences of adopting process mining for organizations need to be analyzed on a technical, individual, group, organizational, and ecosystem level (vom Brocke et al. 2021b), with the need to address non-technical concerns about process mining applications more carefully (Martin et al. 2021). Nevertheless, although there has been much research on how organizations should implement process mining to generate value, organizations still face many challenges. Recent studies have shown that organizations face difficulties in implementing process mining (vom Brocke et al. 2021b; Martin et al. 2021) and in increasing its maturity in organizations (Dunzer et al. 2021; Martin et al. 2021).

2.3 Maturity Models

In order to enhance the maturity of emerging new technologies, such as process mining, maturity models can be used to support the analysis of organizations and processes (De Bruin et al. 2005; Becker et al. 2009). To determine maturity, the domain of interest is separated into specific, measurable, and fundamental factors (Rosemann and De Bruin 2005b). These factors are divided into finer components called elements (Hammer 2007), ordered along a typical evolutionary path with discrete maturity stages, (e.g., from initial to optimizing) (Paulk et al. 1993; Rosemann and De Bruin 2005b). These maturity stages represent different levels of capability in the model's domain. Organizations can position themselves on this scale by evaluating the given elements (Rosemann and De Bruin 2005b; Becker et al. 2009). Ultimately, the application results in the status of the organization. With this as-is assessment, the gap to a to-be maturity can be analyzed (Tarhan et al. 2016). It is important for maturity models to consider which audience is targeted and to enable these user groups to access the model with tools like online surveys or self-assessment possibilities (Becker et al. 2009; Kühn et al. 2013).

Capability measuring maturity models have been applied in different domains since the inception of the

CMM (Capability Maturity Model for Software), introduced in 1991 by Paulk et al. (1991). It was later developed into the CMMI (Capability Maturity Model Integration), a single framework for software engineering process improvements (Paulk et al. 1993; De Bruin et al. 2005; SEI Carnegie Mellon University 2009; Team 2010) and proved applicable (Paulk et al. 1993). Since then, maturity models have been published for many domains, such as innovation management (e.g., Niewöhner et al. 2021), product development (e.g., Gausemeier et al. 2012), and BPM (e.g., Kerpedzhiev et al. 2021). Thus, in recent years, numerous studies on the topic of BPM maturity models have been published (Felch and Asdecker 2020; Röglinger et al. 2012; Tarhan et al. 2016). For the characterization of the BPM capabilities of organizations, six factors are important: information technology and systems, culture, methodology, strategic alignment, people, and governance (Rosemann and De Bruin 2005b). These factors have been recently reviewed and adapted to reflect the influence of digitalization (Kerpedzhiev et al. 2021). In addition, four new factors, namely, process data governance, data literacy, evidence centricity, and process data analytics, were added to the existing ones. Thereby, the latter factor thematizes the value of using advanced data processing techniques such as machine learning to leverage BPM activities (Kerpedzhiev et al. 2021).

To date, only very few maturity models for process mining have been proposed. Often these are developed for specific domains. Jacobi et al. (2020) developed a three-stage maturity model for process mining in a cross-organizational context. The model comprises different application activities for process mining in supply chains, namely, construction, alerting and decision support, and automated adjustments (Jacobi et al. 2020). Because this maturity model primarily focuses on supply chain management, it can be used as a starting point but may not be suitable to being applied in more complex scenarios that involve organizational embedding or data quality. Linden (2021) proposes conditions that include the presence of strategic issues, business cases for process mining of at least one million Euros or Dollars, the possibility to resolve the underlying issues by improving business processes, and an organization that is intent on improvement. While these guidelines are relevant to organizations who seek guidance on whether or not to start a process mining initiative, they neglect a broad range of capability areas (e.g., the capability of an organization to apply process mining is not covered) and the use of different maturity stages. Additionally, these guidelines are not scientifically derived, but are solely drawn from the author's experience (Linden 2021). Further, to successfully implement process mining, different competencies (i.e., technical and business-related) for different roles of process mining practitioners (e.g., head of process mining, process analyst, data engineer) should be considered. Each role is associated with distinct tasks, which translate into varied expectations, use cases, and required capabilities (Kipping et al. 2022). While the authors share insights on the benefits, goals, challenges, and future use cases of leveraging process mining in organizations, they omitted thoughts on how to overcome obstacles (Kipping et al. 2022).

However, research on capabilities and competencies needed for a successful implementation and scaling of process mining is missing (Kipping et al. 2022). To the best of our knowledge, the specific characteristics of applying process mining are not comprehensively reflected in current maturity models. With a growing number of organizations that want to adopt process mining in the long term (van der Aalst and Carmona 2022a), various publications call for more guidance in the form of maturity models to support its implementation (Dunzer et al. 2021; Martin et al. 2021).

3 Research Method

Figure 1 depicts our research method inspired by Becker et al. (2009), including two development and evaluation cycles for the model and two more cycles for developing additional media, such as an online survey and an application method. Additionally, we derived possible actions through qualitative interviews (Myers and Newman 2007) that support organizations in improving their process mining readiness.

While multiple approaches for developing maturity models exist (De Bruin et al. 2005; Mettler 2010; Carvalho et al. 2019), Becker et al. (2009) provide a method for developing IT-related maturity models which draws on the Design Science Research paradigm (Hevner et al. 2004). The method is based on the properties and development history of previous maturity models and covers the steps from the ideation to publishing and usage. It focuses on the understandability and reproducibility of maturity models, while pursuing an iterative approach based on the literature and on implications from the specific context (zur Heiden and Beverungen 2022). Importantly, maturity models are context-sensitive and often become invalid with changing environments and further progress in technologies. Thus, to keep the model up-to-date and relevant, it is necessary to review it frequently. In order to ensure its relevance and accessibility for the target audience, insights were drawn from Kühn et al. (2013) for certain design decisions, e.g., how to make the maturity model accessible. Our target audience are primarily practitioners who want to assess and improve process mining maturity. Nonetheless, researchers

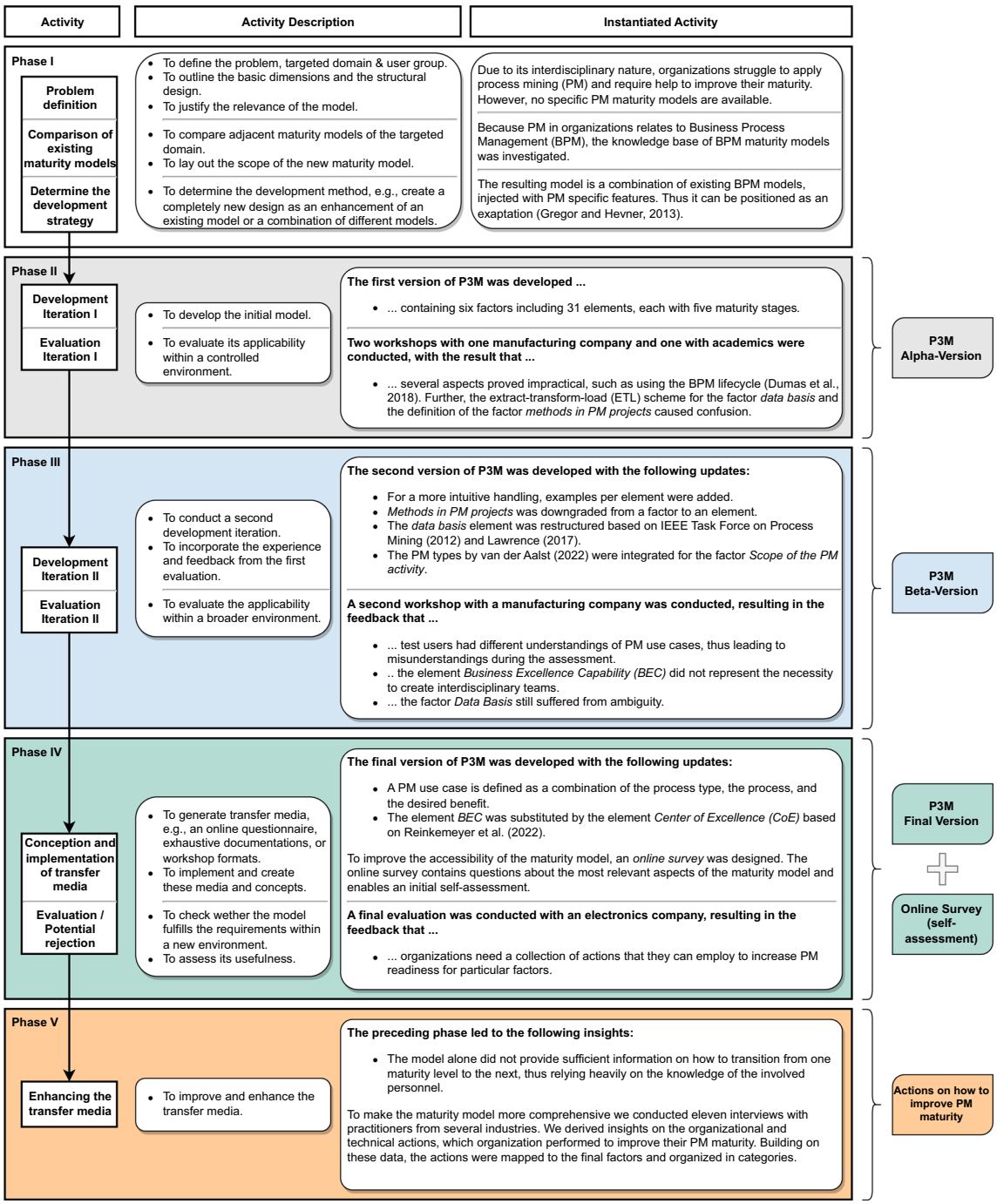

Fig. 1 Maturity model development method (adopted from Becker et al. 2009)

are invited to use our model and to contribute to its improvement in future research.

Starting in April 2021, we instantiated a 30-month development project comprising five phases. The first phase covered the three steps outlined by Becker et al. (2009), including narrowing down the problem definition and gathering requirements by scanning the state-of-the-art maturity models in general and within the BPM domain. Subsequently, we determined the development strategy. We decided for an exaptation (Gregor and Hevner 2013), which draws from the existing BPM maturity models and adopts them to the process mining domain. In the second phase, we developed the first version of the Process Mining Maturity Model (P3M). To further ensure rigor and relevance (Hevner 2007), we collaborated closely with a manufacturing company. The third phase covers the

refinement of the model's factors and elements with the help of the involved organization.

The fourth phase covers the application and evaluation of the final version of P3M. For this purpose, we integrated a second organization, which was not involved prior to this phase. In total, the development team comprised eight people from academia, two business process managers and a data scientist from a manufacturing company, and two process and tool owners from an electronics company. While neither of the involved organizations had made extensive use of process mining in the past, they were proficient in using data-driven methods. The academics' experiences ranged from having applied process mining in several industrial cases to not having used it at all, which allowed us to cover multiple user perspectives .[1]

The fifth phase covers the identification of actions to improve process mining readiness within organizations. We conducted eleven interviews (Myers and Newman 2007) with practitioners from various organizations (cf. Table 1) and interviewed two distinct but interrelated groups of informants. The first group (coined "internal" users) includes participants who employed process mining internally. The second group (coined "external" users) includes participants whose organizations consult and support others in their process mining initiatives. All internal users were in charge of initializing process mining initiatives in their respective organizations, i.e., the ones responsible for establishing process mining in the organization from scratch. Each interview took roughly 60 minutes, asking participants about aspects of P3M and their experience with the respective factors (see Sect. 4), including the introduction of process mining in the respective organization, any accompanying challenges, and how these were addressed.

A team of six researchers thoroughly analyzed the transcripts and identified statements that relate to actions taken by the organizations to improve process mining initiatives. The remaining statements were then processed in four steps. First, a title for each item was identified (e.g., 'create clarity on the organizational embedding'). Second, all items were assigned to a factor of P3M (e.g., all 'create clarity on the organizational embedding' statements were assigned to the organization factor in P3M). Third, the titles of items were adjusted, and similar items were grouped (e.g., the title was changed to 'set organizational embedding'). Fourth, the titles of the groups were transformed into actionable advices by comparing them and their underlying statements to the existing knowledge base (e.g., the name was transformed to 'Anchor initiative in a hybrid setup' based on Reinkemeyer et al. 2022). During the whole process, all relevant items were retained and no exclusions made, for example, because they were only mentioned once in the interviews. Consequently, some groups only refer to one interview. A complete list of the statements from the interviews, their titles, and the derived actionable insights can be found in Sect. 5 and the Online Appendix (available online via http://link.springer.com).

4 Development and Application of the Process Mining Maturity Model (P3M)

The resulting P3M[2] consists of five factors with a total of 23 elements. Figure 2 gives an overview of P3M with its factors *Organization, Data Foundation, Peoples' Knowledge, Scope of the PM Activity* and *Governance* and the corresponding elements and their definitions. Each element has five maturity stages, ranging from *Initial* to *Optimizing* (e.g., adapted to the maturity stages of Paulk et al. 1991 and Rosemann and De Bruin 2005b).

The first and lowest stage, *Initial*, is used for non-existing capabilities or undocumented guidelines. The second stage, *Rudimentary*, often describes a first contact with external consultants or theoretical knowledge that is untested in practice. The third stage, *Standalone*, usually covers first pilot projects undertaken by the organization itself. The fourth stage, *Systematic*, introduces repeatable structures and mechanisms for constant evaluation and improvements. The last stage, *Optimizing*, typically introduces long-term visions and organizational structures that are dedicated to maintaining, improving, and strategically developing the maturity. Typically, when the highest possible maturity stage is reached, the organization will be aware of the options for improvement, will be able to adjust to business needs and market changes, and will have dedicated organizational entities working on different aspects of process mining maturity. The terms coined for the three stages – *Rudimentary*, *Standalone*, and *Optimizing* – were chosen in line with the conventional naming of the CMM (Paulk et al. 1991). To move up from one maturity stage to the next, the previous stage must be fulfilled (Rosemann and De Bruin 2005a). Similar to the CMM, the maturity stages are ordinal in nature (Paulk et al. 1991), which means that the necessary effort to reach the next stage varies between elements and from level to level.

[1] The detailed development process of P3M is outlined in Brock et al. (2023). Subsequently, we slightly adjusted the definitions of the 23 elements based on the additional feedback we received. However, no major changes were implemented as compared to the model in Brock et al. (2023).

[2] The comprehensive maturity model with a detailed examples and descriptions for every factor, element, and maturity stage is available at https://www.its-owl.de/process-mining-maturity-model/.

Table 1 Overview of the interviewed practitioners, their experience, and responsibilities

#	PM User	Industry	Department of the Initiative	# Employees	# Employees in the Initiative	Organization's Experience with PM	Position
I1	External	Software Development	Software Development	10	2	3.5 years	CEO
I2	Internal	Machine-Lending	Order Management	67	4	2.5 years	Controlling & Accounting
I3	Internal	Electronics	PLM Processes & Tools	6000	2	1.5 years	Lead Cross-Divisional Digitalization
I4	Internal	Energy	Meter Reading Operation	1095	10 to 15	3 years	Digitalization Expert for Prozess Automation
I5	Internal	Engineering	BPM	3500	5	1.5 years	Lead Business Process Optimization
I6	Internal	Engineering	IT & BPM	18,143	5	2.5 years	Senior Vice President Corporate BPM
I7	Internal	Electronics	Data Science	9000	18	2 years	Teamlead Complexity Management & Data Science
I8	External	Consulting	Data Science & BPM	190	5 to 10	3 years	Consultant
I9	External	Software Development	Software Development	112,000	100	8 years	Consultant
I10	Internal	Agriculture Engineering	Digitalization	5500	3	3 years	Process Management
I11	Internal	Electronics	Finance & Controlling	6500	2	3 years	Controlling

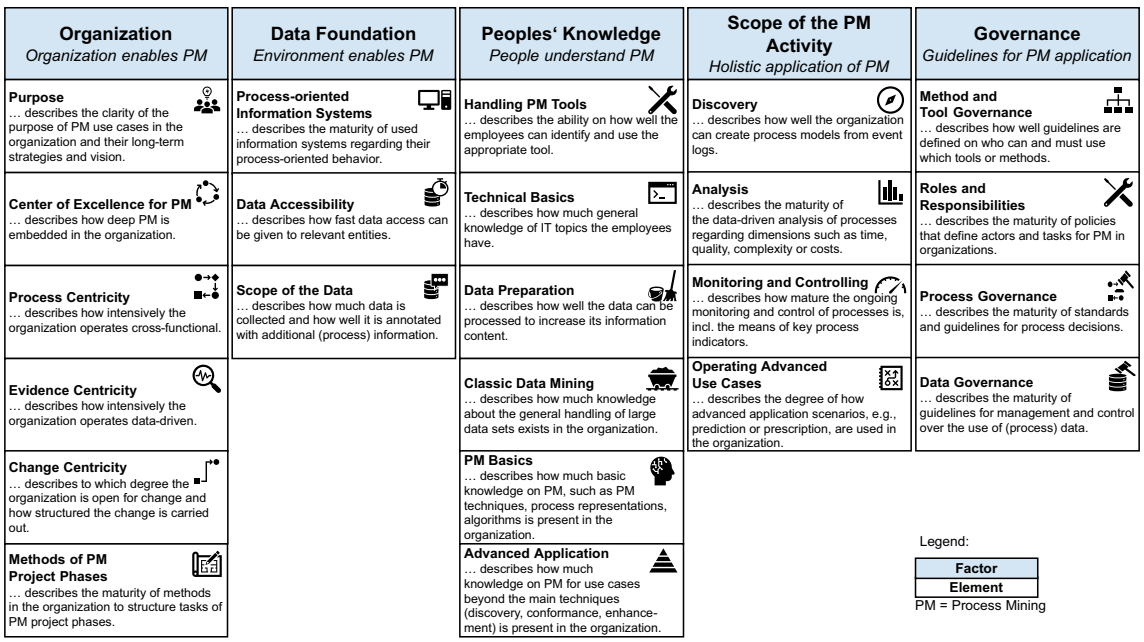

Fig. 2 Overview of the Process Mining Maturity Model (P3M)

How well an organization enables process mining is described in the first factor, *Organization*. It is divided into strategic, cultural, and structural aspects of the respective organization which are reflected in its six elements *Purpose*, *Center of Excellence for Process Mining*, *Process Centricity*, *Evidence Centricity*, *Change Centricity*, and *Methods of Process Mining Project Phases*. Strategically speaking, the element *Purpose* (Reinkemeyer 2020)

captures the clarity of initial process mining use cases and long-term process mining visions. Considering the cultural perspective, the elements *Process Centricity*, *Evidence Centricity*, and *Change Centricity* (Kerpedzhiev et al. 2021) cover the mindset of an organization's ability to think and work in process terms, to base their decisions on facts, and its openness to change. From a structural perspective, the element *Center of Excellence for Process Mining* (Reinkemeyer et al. 2022) captures an organization's maturity in terms of embedding process mining initiatives into its organizational hierarchy (Reinkemeyer et al. 2022; van der Aalst and Carmona 2022b). Various authors (van Eck et al. 2015; Emamjome et al. 2019) have called for more guidance in the practical application of process mining. Therefore, *Methods of Process Mining Project Phases* is an indispensable element that captures an organization's capability to use and maintain methodological guidance for its process mining efforts.

The second factor, *Data Foundation*, consists of the three elements, *Process-oriented Information Systems*, *Data Accessibility*, and *Scope of the Data*. Instead of rating the quality or quantity of event logs, the underlying IT and data environment for process mining efforts is rated. The element *Process-oriented Information Systems* is considered in terms of the maturity of information systems (IEEE Task Force on Process Mining 2012) leading to processes that are completely covered by information systems resulting in high data quality. Additionally, *Data Accessibility*, and *Scope of Data* cover the speed of access (i.e., how quickly data can be retrieved from the environment) and the richness of context data (i.e., how much metadata, additional attributes, or additional information is available) (Lawrence 2017).

The third factor, *Peoples' Knowledge* captures the skills and expertise of individuals in the organization. This factor combines the six elements, *Handling Process Mining Tools*, *Technical Basics*, *Data Preparation*, *Classic Data Mining*, *Process Mining Basics*, and *Advanced Application* (van der Aalst 2016). People in process mining initiatives need to know how modern information systems work, how data is pre-processed, and what challenges and pitfalls can arise concerning data handling. Additionally, to conduct advanced process mining applications, people need to understand classic data mining and machine learning approaches, e.g., such as clustering algorithms.

Which process mining techniques are applied in how many use cases, capturing its intensity and quantity, is covered in the fourth factor, *Scope of the Process Mining Activity*. It is divided into the four elements, *Discovery*, *Analysis*, *Monitoring and Controlling*, and *Operating Advanced Use Cases* (van der Aalst 2022). This factor allows organizations to reflect on the possibilities of process mining techniques for different use cases, and enables them to set a focus of their initiative's efforts, i.e., it is not necessary to use every technique that process mining offers.

The last factor, *Governance*, contains the elements *Method and Tool Governance*, *Roles and Responsibilities*, *Process Governance*, and *Data Governance*, which capture the maturity of rules and regulations within an organization. Just as in regular BPM (De Bruin and Rosemann 2007; Kerpedzhiev et al. 2021), the governance structures define the tools that are used, the typical roles in process mining projects, and the rules for data access and the adaption of processes (e.g., through process owners) (IBM 2007).

The maturity model can be used to assess the as-is maturity of an organization, and to prioritize elements that need to be improved. We validated the maturity model with an organization from the electronics industry with around 7000 employees worldwide. For a detailed introduction to the comprehensive maturity model, we set up an online survey containing questions on the most relevant elements. The online survey was used for the preparation of a detailed workshop, where two process and tool owners, who are responsible for the product lifecycle management, assessed the entire maturity model. All 23 elements were discussed and assessed. After rating their organization's as-is maturity, the participants set the to-be maturity for certain elements. The filled-in maturity model of the organization is displayed in Fig. 3.

Based on the validation and the recognition that dedicated steps on how to apply P3M need to be documented, we derived an application method for the maturity model (see Fig. 4). First, practitioners fill out an online survey, which introduces them to the maturity model. Second, process mining experts can use the survey to prepare and schedule the actual assessment workshop. Third, the workshop is conducted. In the workshop, the as-is and to-be maturity are assessed. Process mining experts should emphasize that the assessment is not seen as a benchmark, but rather as a tool to (re-)focus the organizational activities. Consequently, organizations are free to choose the desired to-be level. In our case example (see Fig. 3), the organization chose to set the to-be stages only one maturity level higher than the as-is stages across multiple elements, even though this is not mandatory. The to-be levels could be set to any target level. Fourth, improvement steps are determined. The exact actions are derived from the individual knowledge of the participating practitioners and involved process mining experts. The actions should be tailored to the needs of the organization. Ultimately, the organization needs to implement the actions to improve its process mining maturity before re-assessing the current as-is maturity.

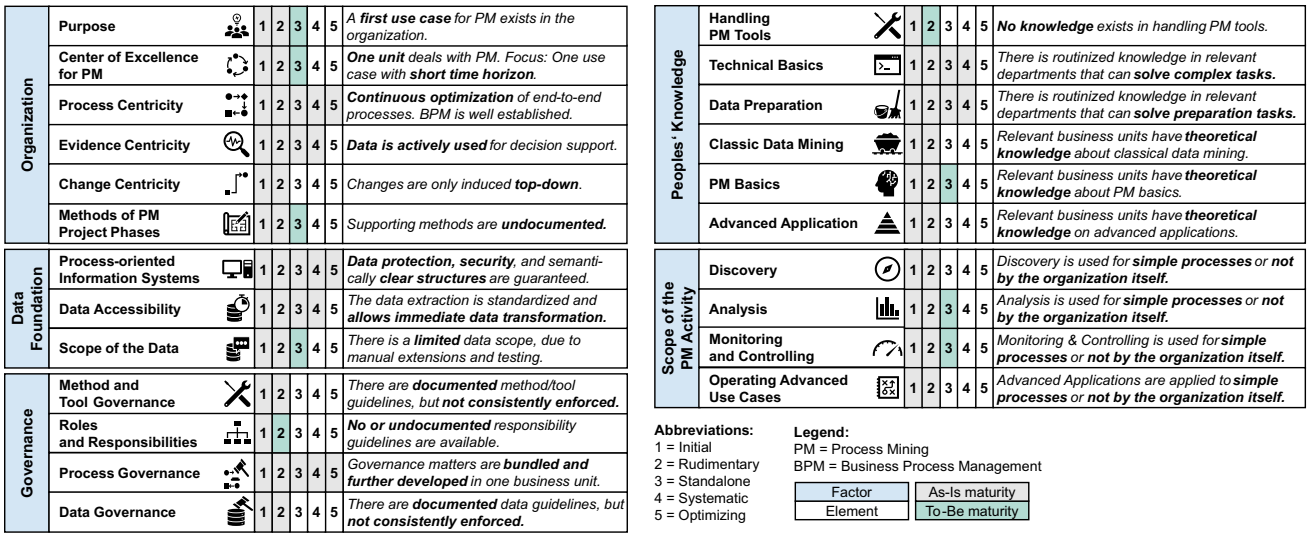

Fig. 3 Applied maturity model of a company from the electronics industry

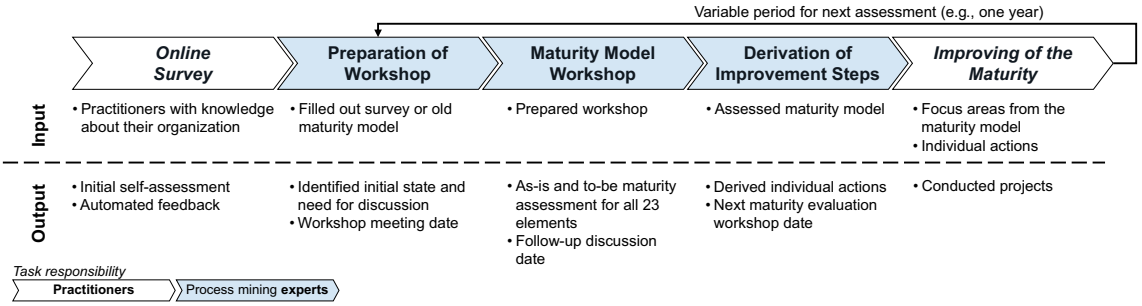

Fig. 4 Application method of P3M

Because we realized during the application of P3M that identifying actions for improvement is difficult and strongly dependent on the knowledge of the involved process mining experts, we conducted interviews with multiple organizations to identify typical actions taken to improve their process mining maturity.

5 Actions to Improve the Process Mining Maturity in Organizations

5.1 Experiences and Lessons Learned From Real-World Process Mining Initiatives

P3M shows that organizations need to constantly improve their process mining activities holistically. To provide actionable insights for improvements of the factors, we subsequently describe common actions identified in the interviews, organized by the factors of P3M.[3]

5.1.1 Organization

A frequently mentioned action taken to increase process mining readiness in an organization is the proper embedding of the process mining initiative.

> "By the end of the day, you need someone who connects IT and business processes. Therefore, the organizational embedding is important and should clarify 'who does it [process mining]?"' ∼Interviewee I5 (O06-01)

While interviewees I5 and I9 (O06-02) reported that in their organization process mining initiatives are affiliated with the BPM departments, interviewees I2 (O06-03) and I10 (O06-04) described their embedding as stand-alone initiatives. The first two (I5 and I9) attached process mining capabilities to individuals in different departments, who then worked together, while the latter two (I2 and I10) reported on a dedicated process mining team. The organization of I11 (O06-05) set up their center of excellence within the finance department. The organization of interviewee I4 (O12-02) introduced a center of excellence with

[3] An overview of all reported actions is available in Tables 3 to 7 in the Online Appendix.

satellites in each of the departments involved. The center of excellence is mostly responsible for system administration tasks, while the satellites work as contact persons in the respective departments. I6 (O10-01) and I10 (O11-01) mentioned similar experiences, reporting on simultaneous process mining initiatives in different divisions of their organization, who communicate via the organization's head office.

Beyond organizational aspects, I6 actively worked on improving process and data understanding in the organization.

> "We have completed a communication campaign. [...] We have made the campaign more human-relatable, because processes and data are rather abstract. We used every day working situations from real colleagues [to show their relation to data and processes]." ∼Interviewee I6 (O02-02)

I7 (O03-01) also highlighted the importance of understanding data and processes. For example, the notion of a case ID had to be explained in detail in every new project. Interviewees I5 (O04-01) and I6 (O04-02) suggested integrating process mining initiatives into larger digital transformation projects (e.g., introducing ERP systems) because such projects often revolve around understanding processes and the respective IT artifacts.

5.1.2 Data Foundation

Three interviewees mentioned that they connected their information systems with a dedicated process mining software, employing the data connectors provided by the software vendor. Interviewee I6 (D06-01) highlighted this as a milestone because it made the data access and transformation process more efficient. Often, this step was performed in collaboration with the process mining software vendor or consultants, as mentioned by I9 (D06-02) and I10 (D06-03). I7 (D08-01) highlighted how their organization set up a dedicated data lake for processing event data from multiple sources.

> "Our data was originally solely extracted from the ERP system. [...] We further push data into a data lake and use it [the data lake] as the central repository and get data from there." ∼Interviewee I7 (D08-01)

Interviewee I4 (D05-01) stressed that the organization gradually integrated more data sources. Most other interviewees indicated that they used data from leading information systems that govern their core processes, such as the ERP or PLM systems, to kick off initial process mining initiatives.

5.1.3 Peoples' Knowledge

Most of the interviewed practitioners reported tool-specific training with the vendor. This is important to get a basic understanding of the tool set. Interviewee I4 (P05-01) mentioned that not all business experts conduct such training. Instead, the first analysis results and dashboards are often developed in a collaboration between trained in-house experts and the respective business experts. This way, knowledge about process mining and tools is diffused within the organization, without having to train every single person in dedicated training sessions. Interviewee I6 (P08-01) reported on the preservation of knowledge in larger organizations. The organization allocated the task of gathering information about lessons learned and best practices from different initiatives in the various divisions to a central person in the corporate head office. Other practitioners such as I4 (P03-02) and I9 (P03-01) also highlighted that they introduced a dedicated role or person to act as an internal multiplier, to gather knowledge from and advice all internal process mining initiatives.

Interviewee I8 (P07-01) reported that the documentation of process mining initiatives should include both technical aspects and the process of interpreting the analysis results. This provides a reliable resource to help externalize knowledge and increase the knowledge transfer in the organization.

> "[We wrote] a documentation sheet that describes our data interpretation process as well as the techniques and methods that were used in projects. This way, they [the consultancy clients] have the collected knowledge or they can look it up." ∼Interviewee I8 (P07-01)

5.1.4 Scope of the Process Mining Activity

Most interviewees highlighted that they identified one relevant process mining technique (mostly process discovery) for their organization and then deployed that technique to different processes. Hence, one frequently discussed topic was how to select the right process for use cases in a process mining initiative.

> "We join the quarterly meetings of the BPM team. [...] There, we showcase our 'service' [the process mining initiative], and invite the BPM team to contact us if help is needed." ∼Interviewee I7 (S05-01)

Other practitioners followed different approaches. While I7 (S03-01) solely identified use cases based on the expected business value, I5 (S02-01) screened the process landscape to identify cases with a sufficient database and expected business value. I11 (S11-01) similarly stressed that

depending on the selected process, the organizational and technological settings change (i.e., business interests change and data is (un-)available). I6 (S01-01) relied on input from sponsors for new use cases, meaning that they got requests from superiors to apply process mining. Regarding new technologies, I8 (S08-01) reported that, from a data science consultancy perspective, new methods, tools, and techniques are frequently screened in order to identify new application scenarios for process mining.

5.1.5 Governance

I5 (G02-01) and I7 (G02-02) mentioned that they involved the works council early on in their process mining initiative, for example, by including them in key meetings to avoid confusion and concerns about possible data privacy concerns. I5 (G04-01) additionally mentioned that writing down agreements is helpful.

> "We created an interims agreement with the works council [regarding data to be used within first projects]. [...] [For the regular usage of process mining] an organization-wide agreement needs to clarify who can use which data for what" ∼Interviewee I5 (G04-01)

Another aspect that was frequently mentioned concerns the implementation of specific roles and responsibilities in process mining initiatives. I7 (G08-01) reported that their organization has a triad of responsibilities and hierarchies: The IT department structures the enterprise architecture and is responsible for the information systems used. The BPM department implements the respective business processes on top of that technical infrastructure by modeling the business processes for the organization and defining how the information systems are used. The data analytics team is responsible for process improvement, data collection, and controlling of the business processes. Therefore, the data analytics team serves as an interface between the IT and BPM departments. I8 (G08-05) reported that they separate the process excellence, the process owner, and the respective business department. Any adjustments to analysis results are conducted by the excellence team. I10 (G08-03) reported to operate in a similar fashion, where analysis results are used by participants, but are only adapted by the process mining initiative itself. In contrast, I11 (G08-06) stressed that they encountered changing roles within their process mining initiative, as the roles and responsibilities evolved throughout different process mining projects. Lastly, I4 (G05-01) highlighted the importance of data security, which becomes particularly important in the later phases of process mining projects. I11 (G05-03) explained that the IT department vetoed providing more access to event data to a third-party tool vendor for multiple reasons, for example, security concerns.

5.2 Actions to Improve Process Mining Maturity

In a dynamic world, process mining has emerged as a valuable tool for the management of process dynamics (Pentland et al. 2021; Wurm et al. 2021). While it is known that various factors can influence the success of process mining projects (Mans et al. 2013; Mamudu et al. 2022), measuring the success of process mining initiatives is rarely undertaken (Linden 2021; Jacobi et al. 2020; Grisold et al. 2020). Hence, scholars and practitioners repeatedly call for process mining maturity models and practical guidance on how to establish process mining sustainably (Emamjome et al. 2019; Dunzer et al. 2021; Martin et al. 2021). Consequently, beyond developing, demonstrating, and validating P3M and it's application method (Becker et al. 2009; Kühn et al. 2013), we derive concrete actions to improve the maturity factors and elements, comprising both technical and social measures. Based on our interviews, we identify 30 possible actions that organizations can perform to improve their process mining maturity. A comprehensive overview of these actions is depicted in Table 2. Subsequently, we briefly discuss the identified actions. Each action is given a distinct identifier based on the factor abbreviation and an incremental number (e.g., A-O1 is the first action for the factor *Organization*).

5.2.1 Actions to Improve the Factor Organization

A commonly mentioned action that strongly impacts the success of process mining is the embedding of the process mining initiative into the organization. We know from recent observations (Galic and Wolf 2021; Reinkemeyer et al. 2022; van der Aalst and Carmona 2022b) that process mining is more effective in organizations that conduct multiple projects simultaneously. Reinkemeyer et al. (2022) provide various options for the embedding of process mining initiatives into the organization. These options are similar to our findings from the interviews. For example, Reinkemeyer et al. (2022) report that both hybrid and centralized initiatives are viable, which strongly correlates to our observations and leads to actions A-O3 and A-O4 in Table 2.

Various authors in related domains such as computer science, data science, and BPM have stressed the importance of management support and sponsorship (Jarrar et al. 2000; Gao et al. 2015; Trkman 2010). Process mining initiatives are no exception (Mans et al. 2013; Mamudu et al. 2022; Martin et al. 2021). Actions taken by the interviewees to secure management support include, for example, presentations of and sensitization for process

Table 2 Identified actions to improve the process mining maturity of organizations

Factor		Action	Explanation		References
Organization	A-O1	Raise awareness in management workshops	Let the top management experience process mining, e.g., by conducting a workshop where they mine an artificial process	I5	
	A-O2	Raise awareness in management circles	Present findings from process mining projects to the management	I8	Mans et al. (2013), Mamudu et al. (2022)
	A-O3	Anchor initiative centrally	One centralized initiative bundles all process mining activities within an organization	I3	Reinkemeyer et al. (2022)
	A-O4	Anchor initiative in a hybrid setup	Connect a centralized initiative to multiple decentralized initiatives, e.g., in the corporate head quarters and branches	I2, I4, I5, I6, I10	Reinkemeyer et al. (2022)
	A-O5	Human-centered communication campaign about processes and data	Highlight the importance of data and processes, e.g., by posting short videos on the intranet	I6	
	A-O6	Involve the IT department early	Communicate with the IT department early, and identify benefits for the them	I5	
	A-O7	Combine the process mining initiative with larger digital transformation projects	Use larger digital transformation initiatives to validate and utilize process mining in an innovative environment	I5, I6	
Data Foundation	A-D1	Implement a central data repository	Initialize a central data infrastructure, e.g., a data lake, to gather event data from different sources	I7, I8, I10	Pingos and Andreou (2022)
	A-D2	Iteratively include new information systems	Do not try to include all information systems at once, but step-by-step	I4	Reinkemeyer (2020)
	A-D3	Implement the connectors to data sources	Utilize the connectors offered by process mining vendors to connect with the leading information system	I6, I9, I10	
	A-D4	Increase data quality with automation	Implement automation (e.g., RPA) to automatically maintain master data and increase data quality	I10	Radke et al. (2020)
	A-D5	Manually export first data for validation	Especially for on premise systems, using connectors is difficult. Manually export data for a low-effort start	I9	
	A-D6	Strive for perfection, deploy pragmatism	Most data can be used as is. Focus on that data to begin with.	I7	
Peoples' Knowledge	A-P1	Determine an internal multiplier	Identify a person or group of persons to collect and share knowledge about process mining within the organization	I4, I6, I9	
	A-P2	Store knowledge in a wiki	Externalize knowledge by documenting it in a knowledge base	I1, I8	
	A-P3	Train domain experts by involving them in the analysis	Train domain experts by including them in the data pre-processing and mining phases	I4	
	A-P4	Conduct trainings with vendors	Conduct the trainings of the respective process mining tool vendor	I3, I5, I8, I9	
	A-P5	Specify trainings for the respective departments	Customize training to the specific needs of different departments (e.g., IT vs. business department)	I8	
	A-P6	Utilize online-classes for self-study	Various online classes on process mining exist, where practitioners can train on particular aspects of process mining	-	
	A-P7	Create a technical and a functional documentation	Create documentations for technical aspects and functional aspects, such as methods used or analysis steps taken	I8	
Scope of the PM Activity	A-S1	Systematically identify new use cases for your initiative	Determine use cases on the basis of benefits, interests, and data availability	I2, I4, I5, I6, I7	Eggers et al. (2021)
	A-S2	Showcase previous use cases to gain attention of business units	Utilize regular meetings to demonstrate the possibilities of process mining to draw business attention	I2, I4, I7	

Table 2 continued

Factor		Action	Explanation		References
	A-S3	Start with process discovery	Start with process mining by applying process discovery, because it is the foundation for other techniques	I4,I8, I9	van der Aalst (2016)
	A-S4	Utilize classical data analytics techniques to gain general insights	Generate ordinary descriptive data analysis plots for domain experts	I8	
	A-S5	Gradually add new use cases to the initiative	Do not overload the organization with too many use cases, but work on them in a step-by-step fashion	I8, I10	
Governance	A-G1	Create short-term data usage agreement	Create a written document in collaboration, e.g., with the works council, for conducting first PoC projects	I5	
	A-G2	Create long-term data usage agreement	Create a written document concerning multiple process mining projects, addressing data and privacy concerns	I5	
	A-G3	Involve the works council early	Involve the works council in the project to show that no individual performance is measured and jobs will not necessarily be rationalized	I5, I7	
	A-G4	Develop a clear set of roles	Aside from classical roles such as process mining or domain expert, also consider roles such as an (analysis dashboard) user	I7, I8, I9, I10	Kipping et al. (2022), van Eck et al. (2015)
	A-G5	Select the right process mining tool	Consider various aspects when selecting a vendor, and do not hesitate to test multiple vendors	I10	Drakoulogkonas and Apostolou (2021)

mining in management circles (A-O2). One practitioner (I5) mentioned that he used a management workshop to raise awareness for process mining by getting management to assemble a product, track the steps digitally, and then apply process mining to show the as-is process in real-time (A-O1).

5.2.2 Actions to Improve the Factor Data Foundation

Process mining is fuelled by data. Hence, the first challenge outlined by the IEEE Task Force on Process Mining (2012) concerns the extraction, merging, and cleaning of data. Accordingly, several of our interviewees were concerned with establishing a reliable pool of event data as a basis for process mining projects. The implementation of data pools ranges from classical data lakes to creating 'universal' connectors for all information systems. Regarding IT infrastructure, Pingos and Andreou (2022) provide an overview of a suggested architecture for an event data lake. We collectively summarize these actions in A-D1.

Additionally, a number of our interviewees stressed that new data sources should be added gradually, aligning with recommendations made by Reinkemeyer (2020), who suggests first analyzing processes with a single data source. We included this action as A-D2. Often, data quality issues play a key role in process mining projects. One concrete action to address data quality issues is using automation techniques like RPA to address master data issues. Radke et al. (2020) demonstrate how RPA can be used to, e.g., check e-mails for new pricing lists and update the master data accordingly. We included this aspect as action A-D4.

5.2.3 Actions to Improve the Factor Peoples' Knowledge

Various actions for knowledge building, transfer, and preservation to and from different process mining participants were mentioned in the interviews. One commonly cited action to increase knowledge about process mining was to put on training courses offered by vendors (A-P4). Additionally, instead of sending various employees to such courses, domain experts can be educated within the organization by including them in the data pre-processing and analysis (A-P3). In this way, domain experts gain first-hand experience of process mining prospects. Surprisingly, none of the interviewees mentioned Massive Open Online Classes (MOOC).[4] Given that many of these are free of charge, we added MOOC as A-P6. Beyond documenting technical aspects, practitioners should also document social and methodological aspects (A-P7). This includes best practices, methods used in projects, and how and which analysis results were derived. This helps to improve projects in the long run and externalize acquired knowledge.

[4] A frequently updated list of MOOC can be found at https://www.processmining.org/courses.html

5.2.4 Actions to Improve the Factor Scope of the Process Mining Activity

Deciding upon a suitable use case for process mining initiatives is important for their success (Reinkemeyer 2020). Our interviews revealed that practitioners select suitable use cases from a diverse pool of influencing factors. Often, a mixture of business benefits, data availability, and domain interest play a role. Eggers et al. (2021) present a taxonomy in which these factors can be systematically rated to derive a classification of the effort and benefit of process mining projects. This is summarized in action A-S1. Additionally, as process discovery is often the first technique used, we suggest to begin with the technique process discovery (A-S3). This is hardly surprising, given that process discovery is often referred to as the first conducted main technique of process mining (van der Aalst 2016), and that algorithms for the discovery were the first to have been developed for process mining (van der Aalst et al. 2004).

5.2.5 Actions to Improve the Factor Governance

While the academic literature frequently discusses privacy-conserving techniques, concepts, and algorithms from a technical perspective (Pika et al. 2020; Mannhardt et al. 2019, 2018), few publications take up an organizational perspective. In our interviews, we identified that short- and long-term agreements between work councils and process mining initiatives can prevent misunderstandings and reduce the need for privacy conserving techniques (A-G1 and A-G2). Such agreements ideally stipulate which data can or can not be used and under which conditions. Ideally, initiatives should include the works council (A-G3) and should clarify that data are not used to measure the performance of individuals and that typical process improvement projects do not aim to reduce the workforce. A clear set of roles in process mining initiatives is vital (A-G4). Different responsibilities and skills are needed in process mining projects (Kipping et al. 2022). The interviews revealed that the role of the expected user of a process mining tool or analysis has important implications for its development, e.g., the graphical interface of dashboards. Lastly, action A-G5 is about the selection of the right process mining tool. Various factors, such as licensing and techniques offered, influence the decision on a process mining tool (Drakoulogkonas and Apostolou 2021). Practitioners should not hesitate to re-evaluate choices and try out different vendors before making a decision.

In summary, we collated various actions that organizations can take to improve their process mining maturity and turn their intentions into actions and apply process mining successfully. While some of these actions are regularly discussed in scholarly publications (e.g., creating a center of excellence), others received limited attention (e.g., effective process mining training). Practitioners can employ these actions in combination with the maturity model for guidance on how to improve the maturity of their process mining initiative.

6 Discussion

6.1 Theoretical Implications

The question of how organizations can effectively manage business processes in a digitalized and hyperconnected world (Beverungen et al. 2021), in which processes tend to drift (Pentland et al. 2020) and embrace unintended and unforeseen dynamics (Grisold et al. 2022b; Pentland et al. 2021), remains an urgent challenge. While one view is to adapt and enhance BPM capabilities (Kerpedzhiev et al. 2021), emerging technologies such as process mining offer a powerful tool for organizations to become more responsive to change. By developing P3M and the identified 30 actions, we directly address recent calls for action and simultaneously open up a wide range of future research and practical application paths. Subsequently, we discuss our twofold contribution and its implications for research on the management of business processes in an increasingly volatile and dynamic environment.

First, we developed P3M in an iterative design process involving multiple workshops and two design iterations in collaboration with two real-world organizations. The model is an exaptation (Gregor and Hevner 2013) derived by synthesizing insights from existing maturity models, industry best practices, and other conceptual frameworks. The development process was strategically guided by the principle of clarity and comprehensibility (Becker et al. 2009; Kühn et al. 2013). This framing highlights the substantial contribution made by P3M in providing a comprehensive framework for assessing and enhancing process mining maturity.

Drawing inspiration from BPM capability models (Rosemann and De Bruin 2005b; Kerpedzhiev et al. 2021), we integrated factors such as *Organization*, *Peoples' Knowledge*, and *Governance* into the model. Some factors, such as *Governance*, remain consistent with the BPM capability models. Other core elements from the BPM capability models (Kerpedzhiev et al. 2021), such as strategic alignment and culture, were aggregated into a single factor called *Organization* to reduce complexity. In response to ongoing discussions surrounding process mining in organizations (Reinkemeyer et al. 2022; Mans et al. 2013; Mamudu et al. 2022), we introduced additional elements, such as *Center of Excellence for Process Mining*

and *Methods of Process Mining Project Phases*. These adaptations demonstrate the model's validation and evaluation in situ during the development process, in pursuit of the overall goal of meeting organizational needs. Concerning the element *Data Foundation*, we draw on insights from existing data maturity frameworks (Lawrence 2017; IEEE Task Force on Process Mining 2012). When it comes to required knowledge of individuals, we draw on the aspects discussed in van der Aalst (2016) to identify the essential skill sets, including basic knowledge about *Classic Data Mining*. Regarding the *Scope of the Process Mining Activity*, we adapted the six types of process mining outlined by van der Aalst (2022). Notably, we consolidated comparative, predictive, and action-oriented process mining into a single element termed *Operating Advanced Use Cases*. This aggregation has proven advantageous, especially in discussions with academics, as it also encompasses emerging process mining technologies, such as object-centric process mining and simulation. We introduced five maturity stages, which are aligned with the framework presented by Paulk et al. (1991). However, we opted to renamed the stages to better encapsulate maturity levels in process mining projects, thereby increasing clarity for practitioners. This strategic renaming proved advantageous, particularly since other maturity models also use five stages. For example, the event log maturity model (IEEE Task Force on Process Mining 2012) also uses five levels, which resembles the element *Process-oriented Information Systems*.

Second, we contribute a collection comprising 30 possible actions that organizations can perform to improve their process mining maturity. These actions support organizations in addressing common challenges related to process mining initiatives. Our recommendations align with previous observations in research and practice. Practitioners in our interviews are particularly concerned about the organizational embedding of their process mining initiatives (Grisold et al. 2021; Martin et al. 2021), often mentioning it as a key success factor (Mamudu et al. 2022). We found that organizations follow common patterns to embed their initiatives, such as implementing hybrid or centralized setups (Reinkemeyer et al. 2022). Larger organizations with decentralized corporate structures especially tend to opt for a hybrid embedding of their initiatives. Another frequently discussed challenge is data quality (Grisold et al. 2021; Martin et al. 2021). We found that practitioners are aware of this challenge and consequently are taking actions to address it (e.g., by manually re-labeling data) or circumvent it (e.g., by identifying use cases where data is readily available). Surprisingly, no actions were identified that aim to address challenges arising from increased process transparency achieved through process mining, such as distrust of process participants, albeit other studies identify a need from practitioners to address such issues (Grisold et al. 2021; Martin et al. 2021).

By zooming out and putting the results into a broader perspective, it becomes apparent that our twofold contribution resolves existing paradoxes within the BPM discipline (Beverungen et al. 2021). These paradoxes arise from the increasing complexity of managing business processes caused by the interconnectivity among actors, processes, and organizations (Beverungen et al. 2021), which accelerate process drift and dynamics (Grisold et al. 2022b; Pentland et al. 2020). The seven paradoxes refer to 1) the increasing complexity of business processes and a need for more frequent updates, 2) the missing capability of process models to easily display complexity, 3) the need for real-time decision-making in processes based on scattered data sources, 4) the need for real-time decision-making and safety requirements, 5) the increasing complexity of IT artifacts, 6) the dichotomy between the need for more standardization without neglecting the added value of individual processes, and 7) the implications of complex environments on design-oriented research. The paradoxes two (focus on process models), four (focus on safety requirements), six (focus on new theories and artifacts within the BPM discipline), and seven (focus on DSR) do not directly address the dynamics of business processes. In contrast, paradoxes one, three, and five outline challenges imposed by the increasing dynamics of business processes. P3M and the 30 possible actions play a crucial role in resolving paradoxes one, three, and five, which have hitherto received limited attention in academia while representing critical challenges for organizations that need to be solved.

Paradox one highlights the challenge of increasing process complexity alongside the need for more frequent process updates due to growing drift and dynamics in business processes (Beverungen et al. 2021). We posit that process mining can play a pivotal role in the early detection of process drift (Sato et al. 2021), enabling organizations to make ad hoc updates, especially in times when exogenous shocks occur more frequently and challenge organizations in how they conduct their business (Röglinger et al. 2022). Ultimately, process mining can be employed in multiple phases of the BPM lifecycle (Dumas et al. 2018; Lashkevich et al. 2023) and allows for more frequent updates of the to-be process models (Martin et al. 2021). Additionally, implementing object-centric process mining (van der Aalst 2019) or event abstraction (van Zelst et al. 2021) can help display or decrease the complexity of processes.

Paradox three revolves around the need for real-time decision-making in processes based on a scattered data base (Beverungen et al. 2021). Undoubtedly, process mining represents the state-of-the-art solution for resolving

this paradox. A plethora of predictive and prescriptive process mining techniques already exist that support real-time decision-making in business processes in specific contexts (Di Francescomarino et al. 2018; Kubrak et al. 2022). In line with recent findings by Brennig et al. (2024), we postulate that enabling organizations to improve the quality of their process mining initiatives will ultimately result in faster, better-informed decision-making.

Paradox five addresses the challenge of designing and implementing complex IT artifacts in the face of limited organizational capabilities and resources (Beverungen et al. 2021). It has been demonstrated that process mining can serve as a valid approach to support digital transformation efforts in organizations (Martin et al. 2021; Grisold et al. 2021; Boenner 2020). For example, Mamudu et al. (2023) find that organizations use PM to establish reporting capabilities about their digital transformation, and Geyer-Klingeberg et al. (2018) demonstrate that process mining can effectively support the development of RPA solutions. More generally, Fischer et al. (2021) utilize process mining to calculate indicators on an event log to identify whether a business process should be optimized centrally or locally by concentrating the organization's resources on the relevant business processes.

We argue that P3M and the 30 possible actions support organizations in their effort to establish the required process mining capabilities. Our findings empower organizations to effectively plan, execute, and manage the development and implementation of process mining activities. The identified factors and described actions assist in identifying and allocating necessary resources while also ensuring that scarce resources are directed toward the most promising activities within process mining initiatives.

6.2 Practical Implications

Current process mining research focuses on developing new algorithms (vom Brocke et al. 2021b), thereby often neglecting organizational aspects (Martin et al. 2021). P3M provides organizations with the possibility to reflect on the maturity of their process mining activities, and the 30 actions support them in overcoming the intention-action gap in their initiatives. However, because every organization has individual structures and characteristics (Reinkemeyer et al. 2022), is bound to environmental conditions (Mamudu et al. 2022), and expects specific benefits from process mining (Badakhshan et al. 2022), the identified actions are diverse and need to be contextualized if implemented. Some of the actions contradict each other and cannot be implemented simultaneously (e.g., A-03 'Anchor initiative centrally' and A-04 'Anchor initiative in a hybrid setup'), but might be implemented at different points in time. Thus, practitioners should view the actions as inspiration and adapt them to their specific needs. Because of the needed contextualization, we include as many actions as possible, even when they are only mentioned by one interviewee.

Our group of interviewees comprises internal and external users, sometimes resulting in different actions (see Table 2). We observed that the external interviewees (I1, I8, and I9) addressed the factors *Data Foundation*, *Peoples' Knowledge*, and *Scope of the Process Mining Activity* more frequently (i.e., between 50% and 83% of their actions) than the factors *Organization* and *Governance* (i.e., between 14% and 40% of their actions). We assume that this divide refers to the fact that governmental and organizational aspects are unique to an organization that wants to apply process mining internally, which makes it more challenging for external process mining experts to specify actions for these factors. Interviewee I9 also highlighted that they normally first get involved once the customer has decided to engage with process mining. Furthermore, as external process mining experts have probably gained more experience through various process mining projects, they are more knowledgeable about the essential infrastructure and data, enabling them to bring up these aspects more frequently. Still, there are similarities between the stated actions of the internal and external interviewees. For example, both reported on the connection of process mining tools via connectors and outlined the importance of installing a multiplier within the organization.

Improving an organization's process mining maturity by employing the identified actions also impacts the dynamics of an organization's business processes. The actions enable organizations to overcome the challenges of implementing, adopting, and managing process mining initiatives (vom Brocke et al. 2021b; Martin et al. 2021). By maturing process mining capabilities, organizations can respond more dynamically to changes in their processes (Pentland et al. 2021; Wurm et al. 2021) and gain valuable insights into process performance (Grisold et al. 2020; Wurm et al. 2021; Kipping et al. 2022). Our data have revealed that organizations that managed to improve process mining capabilities have become more dynamic in handling their business processes. Thus, process mining has increased the flexibility of BPM to manage ever-accelerating and more complex process dynamics (Grisold et al. 2022b; Kipping et al. 2022).

7 Conclusion, Limitations, and Outlook

Organizations need to adapt business processes more flexibly to manage ever-increasing process dynamics.

Process mining is a promising means to establish evidence-based BPM in organizations (van der Aalst 2022). Organizations that manage to implement process mining successfully and sustainably gain valuable insights into the dynamic performances of process activities (Grisold et al. 2020; Pentland et al. 2021; Wurm et al. 2021; Röglinger et al. 2012), enabling them to increase their business value through process optimization (Badakhshan et al. 2022).

In this paper, we develop P3M, a process mining maturity model, consisting of five factors and a total of 23 elements. Each element has five distinct maturity stages. The model is an exaptation from established capability models and best practices from the BPM discipline, data science, and process mining. We prove the usefulness of the maturity model by applying it in real-world organizations. With the intervention, we demonstrate how the application method can be employed to derive focus areas and actions for improvement in organizations. To provide practitioners with more guidance, we conducted eleven interviews to identify measures taken by organizations to improve their process mining maturity. Based on the interviews, we derived 30 actions for each factor of P3M that organizations can implement to improve their process mining maturity.

Naturally, our results are subject to limitations. Although P3M was developed and validated with real-world organizations, applying it to other organizations or domains might lead to the refinement of the model. Especially collecting a large data set of the model's application would enable adjustments to be made to the model (Becker et al. 2009). Additionally, the rather small size of the interview group, and the focus on German organizations, may present a narrow view of process mining initiatives. Hence, we present a preliminary set of actions in this paper. In the future, other researchers can enhance the derived actions by, for example, applying the model in diverse contexts. We believe further, that research is needed to clarify similarities and differences between actions of internal and external user groups to improve process mining maturity in organizations.

While we argue that the current model can significantly support organizations in managing increasingly dynamic business processes, a natural step for its enhancement involves enabling dynamic maturity assessments. Currently, the model facilitates a static snapshot assessment. However, future iterations may encompass adaptable variants that can be tailored to specific needs within specific contexts aligned with organizational needs. Moreover, gathering rich data through conducting maturity assessments with the model could help to predict future maturity stages. Performing a scenario analysis based on predictions holds immense potential, as it could empower organizations to evaluate transformation paths in advance.

Furthermore, we assume that maturity archetypes for organizations exist, which could be used to guide organizations through a long-term development process, sustainably maturing and improving process mining activities. Studying transformation paths in longitudinal case studies would be one interesting step for future research. Furthermore, identifying the weighted relevance of the model's elements to calculate the aggregated maturity levels, for example, seems promising.

Reflecting on the discussion of our results, we did not find any literature concerning the systematic training and education of employees in organizations. Additionally, we observed that, although some reported issues (such as using RPA for improving master data) are addressed in scholarly publications, practitioners are not aware of them. We call for future research to investigate the systematic training of employees in more depth, and, to fill the intention-action gap, to make results better accessible for practitioners.

P3M provides a unique platform for future research and development to mature the process mining domain in theory and practice. Employing a typical scale for classifying maturity models (De Bruin et al. 2005), our model is currently characterized as descriptive. However, the outlined actions for enhancing maturity are an initial step towards augmenting the model with prescriptive elements. By integrating our model with these actions, future maturity levels and their corresponding transformation paths can be defined.

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