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A process mining maturity model: Enabling organizations to assess and improve their process mining activities

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A PROCESS MINING MATURITY MODEL: ENABLING ORGANIZATIONS TO ASSESS AND IMPROVE THEIR PROCESS MINING ACTIVITIES

Research Paper

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Abstract

Organizations employ process mining to discover, check, or enhance process models based on data from information systems to improve business processes. Even though process mining is increasingly relevant in academia and organizations, achieving process mining excellence and generating business value through its application is elusive. Maturity models can help to manage interdisciplinary teams in their efforts to plan, implement, and manage process mining in organizations. However, while numerous maturity models on business process management (BPM) are available, recent calls for process mining maturity models indicate a gap in the current knowledge base. We systematically design and develop a comprehensive process mining maturity model that consists of five factors comprising 23 elements, which organizations need to develop to apply process mining sustainably and successfully. We contribute to the knowledge base by the exaptation of existing BPM maturity models, and validate our model through its application to a real-world scenario.

Keywords: Process Mining, Maturity Model, Business Process Management, Real-world scenario

1 Introduction

In challenging times, it is increasingly important for organizations to control and monitor their business processes (Röglinger et al., 2022). Only organizations that can design their processes transparently and adapt them quickly will be successful (Beverungen et al., 2021). Due to the increasing digitalization of business processes and availability of data in organizations, the standard methods of business process management (BPM) can be enhanced to control and monitor business processes from a data-driven perspective (Dumas et al., 2018). The application of process mining can serve as a viable problem-solving approach for analyzing business processes (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016).

Process mining can be seen as a mix between data science and process science, with the tasks to discover, monitor, and improve processes in organizations (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016). This creates the opportunity for organizations to analyze as-is processes, instead of pre-designed to-be process models (van der Aalst, 2016). Process mining analyzes data that are recorded while executing business processes in information systems and are stored in event logs (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016). Because of this great potential, recent years have shown an increasing interest in process mining, both from academia and practitioners (Emamjome et al., 2019; Reinkemeyer, 2020).

Even though process mining is already used in organizations, many organizations still experience major challenges (e.g., lack of management support, poor data quality, or complex data preparation, Martin et al., 2021) accompanying its application. Thus, its potential for producing business value still remains unknown to organizations (Badakhshan et al., 2023). Consequently, calls for the development of process mining related maturity models exist (Dunzer et al., 2021; Martin et al., 2021). Maturity models are considered an essential tool for determining the status of an organization, deriving actions for improvement, and making intra- and inter-organizational comparisons (Felch and Asdecker, 2020). Such models can serve as a structured approach for initiating and supporting short-term operational projects while also facilitating long-term strategic changes (Felch and Asdecker, 2020). While a large number of maturity models already exist in the area of business process management (e.g., Rosemann and De Bruin (2005b), or Hammer, 2007), their coverage of process mining related aspect is limited (Tarhan et al., 2016; Felch and Asdecker, 2020). However, organizations and researchers might benefit from a descriptive and prescriptive maturity model, implying the need for further research and development (Dunzer et al., 2021).

This paper presents a multi-factor maturity model for assessing and improving the maturity of process mining activities in organizations. The model contains five factors with a total of 23 elements each with five distinct maturity stages. From a theoretical perspective, we contribute an exaptation (Gregor and Hevner, 2013) based on preceding models of the BPM domain. We enhance these BPM capability areas, integrating aspects from data science and process mining. To the best of our knowledge, a comprehensive, multi-factor process mining maturity model is not available in the current knowledge base. Considering a managerial perspective, our findings guide organizations in reviewing and classifying their current state in applying process mining. Further, organizations can set goals and identify their next steps to reach a certain maturity level, by defining specific requirements. By providing detailed explanations and definition for every factor, element, and maturity stage, our proposed model is particularly designed for process mining practitioners. Through our evaluation and demonstration of the maturity model on a real-world scenario, we ensure practical relevance.

The paper is structured as follows. In section 2, we review the fundamentals of process mining and maturity models, which includes the application of maturity models in BPM and process mining so far. Section 3 outlines the applied research method in detail and describes its application in our paper. In section 4, we present our maturity model for process mining in organizations and demonstrate it on a real-world scenario. In section 5, we discuss implications for theory and practice before concluding the paper in section 6.

2 Related Work

2.1 Process Mining

When an organization is concerned with the process-based control and management of work, BPM plays a fundamental role. BPM is intended to support corporate goals and enable targeted control of business processes within an organization (Dumas et al., 2018). Dumas et al. (2018, p. 5) define a business process as a *"collection of inter-related events, activities, and decision points that involve a number of actors and objects, which collectively lead to an outcome that is of value to at least one customer."* As a consequence of the digital transformation, information systems are increasingly intertwined with business processes (Pentland et al., 2020). Accordingly, organizations can analyze data that are stored in information systems in the form of event logs to get insights into process behavior (van der Aalst, 2016).

The goal of process mining is to use event data to extract process-related information to answer questions about processes as well as to discover interactions between the people involved in the process (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016). Therefore, the application of process mining requires that a business process is executed with the help of information systems. The data generated by information systems can be transformed into the form of event logs, which store information about the execution of business processes and reflect the sequence of activities performed, with each activity being uniquely assigned to a process instance. To enable a better view of the real process, as-is process models can automatically be generated from an event log using process discovery (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016; Dumas et al., 2018). The identification and analysis of deviations can be achieved by applying conformance checking where an existing process model is compared to an event log of the same process. Further, the quality of process models can be improved through enhancement, aiming to extend, improve, and enrich existing process models (IEEE Task Force on Process Mining, 2012; Marquez-Chamorro et al., 2018; Weinzierl et al., 2020).

Additional process mining types have been established in recent years dealing with the comparison, prediction and prescription (also called action-oriented) of business processes (Marquez-Chamorro et al., 2018; Weinzierl et al., 2020; van der Aalst, 2022). These methods and techniques enable organizations to analyze their processes quickly and comprehensively, not only in an offline but also in an operational context. Organizations can benefit from process mining by reducing their process costs and execution times, for example by eliminating bottlenecks (IEEE Task Force on Process Mining, 2012). Badakhshan et al. (2023) analyzed how process mining features create action potentials for organizations (theory of affordance). The authors investigate the connection of process mining features, affordances, and value generation, and find that the organizational structures and governance is perceived as an important factor when creating value with process mining (Badakhshan et al., 2023).

Process mining is an interdisciplinary approach that originates from the field of data science and process science. It deals with the modeling and analysis of business processes, with the tasks to discover, monitor, and improve business processes in organizations (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016). Thus, process mining adds the process perspective to existing machine learning and data mining methods and the data perspective to existing process management methods (IEEE Task Force on Process Mining, 2012; van der Aalst, 2016), creating the opportunity for organizations to look at real-world processes, instead of assumed ones (van der Aalst, 2016). In practice, this interdisciplinarity of process mining often requires different business units like IT, BPM, or a respective business department to collaborate (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 use of process mining, a dedicated department is beneficial to accelerate adoption and concentrate resources (Reinkemeyer et al., 2022). Hence, conducting successful process mining projects relies on numerous factors. Mans et al. (2013) propose the six success factors project management, management support, structured process mining approach, data and event log quality, resource availability, and process miner expertise. Mamudu et al. (2022) recently reviewed these success factors and identified three additional factors comprising change management, tool capabilities, and training.

Additionally, the focus of the three factors management support, resource availability, and process mining expertise was adapted and restructured, resulting in the three factors stakeholder support and involvement, information availability, and technical expertise.

In summary process mining enables organization to leverage on their already present event data in IT-systems, by providing as-is business processes, metrics, or improvement opportunities about their business processes. How exactly organizations create value by affording these features is not yet fully understood, but first insights suggests that the governance and organizational structures play a guiding role (Badakhshan et al., 2023). Consequently, successful process mining projects require a diverse set of competences in the fields of organizational structures, data and information prerequisites, and knowledge about tools and process mining (Mans et al., 2013; Mamudu et al., 2022).

2.2 Maturity Models

Maturity models support the analysis of organizations or processes (De Bruin et al., 2005; Becker et al., 2009). To extract maturity, the domain of interest is separated into influencing, measurable, and fundamental factors (Rosemann and De Bruin, 2005b). These factors are split up into finer components called elements (Hammer, 2007), ordered in a typical evolution path with discrete maturity stages (e.g., from initial to optimizing) (Paulk et al., 1993; Rosemann and De Bruin, 2005b). The maturity stages separate different levels of capability in the model's domain. Organizations position themselves on that scale by evaluating the given elements (Rosemann and De Bruin, 2005b; Becker et al., 2009). Ultimately, the application of an assessment model or method 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).

Maturity models can be divided into descriptive, prescriptive, and comparative models. Descriptive models solely assess the as-is level, prescriptive models offer desirable future maturity levels with insightful approaches, and comparative models support internal or external benchmarking. Often, all three aspects are covered in a maturity model's lifecycle (De Bruin et al., 2005). These levels comprise a baseline, which each maturity model should fulfill, a second level for descriptive maturity models, and lastly the highest level for prescriptive maturity models. 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 survey or self-assessment possibilities (Becker et al., 2009; Kühn et al., 2013). Kühn et al. (2013) further stress that, depending on the general design of the maturity model, the required time for the application of the maturity model can take a different amount of time. Capability measuring maturity models have spread 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; CMMI Product Team, 2010) and proved applicable by Paulk et al. (1993). Since then, maturity models have been published for many domains, such as innovation management (e.g., Niewöhner, 2021), product development (e.g., Gausemeier, 2012), and BPM as discussed in the next section.

2.3 Maturity Models in Business Process Management and Process Mining

Numerous BPM maturity models and aggregating studies on the topic of BPM maturity models have been published. Felch and Asdecker (2020), Röglinger et al. (2012), and Tarhan et al. (2016) give an overview and a reflection about maturity models in BPM. Rosemann and De Bruin (2005b) identify six factors which characterize the BPM capabilities of organizations. Those factors are Information Technology and Systems, Culture, Methodology, Strategic Alignment, People, and Governance. Kerpedzhiev et al. (2021) recently reviewed these factors, and adapted them regarding digitalization. The result of the updated BPM capability framework is displayed in Figure 1. The bars next to the capabilities indicate whether the capability is unchanged (white bar), adapted (red-white stripes) or new (red) compared to Rosemann and De Bruin (2005b). The influence of the digitalization is observable in the various factors, with Process Data Governance, Data Literacy or Evidence Centricity being added.

Additionally, Process Data Analytics thematizes the value of using advanced data processing techniques such as machine learning to leverage BPM activities.

Regarding maturity models in process mining, only a few approaches exist. Jacobi et al. (2020) developed a maturity model for process mining in a cross-organizational context. 34 papers of process mining in supply chains were analyzed and classified into a three-stage maturity model (Jacobi et al., 2020). The model is based on process mining activities for operational support: detect, predict, and recommend, concluding three stages, construction, alerting deviations, and automated adjustments (IEEE Task Force on Process Mining, 2012; Jacobi et al., 2020). Since the authors did primarily focus on supply chain management, the maturity model can be used as a starting point but does not allow its application in more complex scenarios that involve organizational embedding or data quality. Kipping et al. (2022) describe the competencies needed to get started and scale up process mining. Interviews with different process mining practitioners were held to determine for each role, what tasks, required skills, and technologies are necessary to succeed. Furthermore, insights about benefits, goals, challenges, and future use cases are given (Kipping et al., 2022). The authors elaborate on specific roles and their competencies but leave out how to overcome obstacles. Linden (2021) postulates three conditions that need to be met in order for an organization to start a process mining initiative based on his experience in the industry. The first condition is a certain organizational maturity, the second condition is data availability, and the third condition is the presence of variation within the business processes. The organizational maturity can be evaluated against the background of four aspects: 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 the business processes, and an organization that has the will to improve itself. While the guidelines from Linden (2021) are very relevant to organizations who seek guidance on whether to start a process mining initiative or not, the author does not provide a broader variety of capability areas (e.g., the capability of an organization to apply process mining is not covered) and no maturity stages are provided. Additionally, these guidelines are not scientifically derived, but are based on the authors experience.

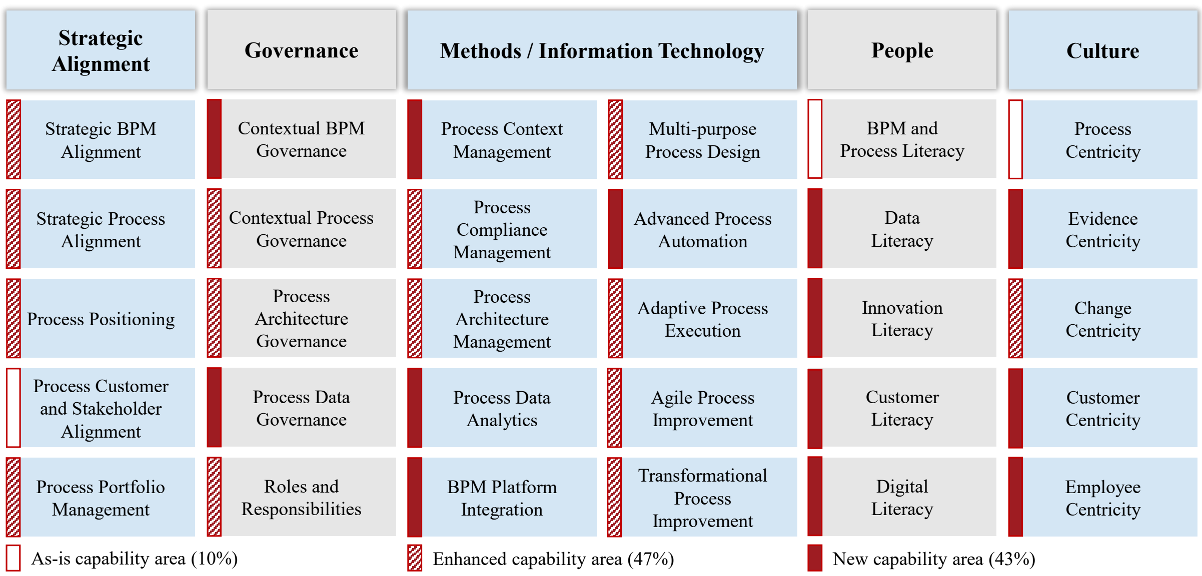

Figure 1 BPM capability framework (Kerpedzhiev et al., 2021, p. 89)

However, to the best of our knowledge, specific characteristics of applying process mining are not comprehensively reflected in current maturity models. With the growing number of companies that need to adopt process mining in the long term (van der Aalst and Carmona, 2022), various publications call for more guidance in form of maturity models to support organizations in long-term process mining initiatives (Dunzer et al., 2021; Martin et al., 2021).

3 Research Method

Figure 2 depicts our research method inspired by Becker et al. (2009).

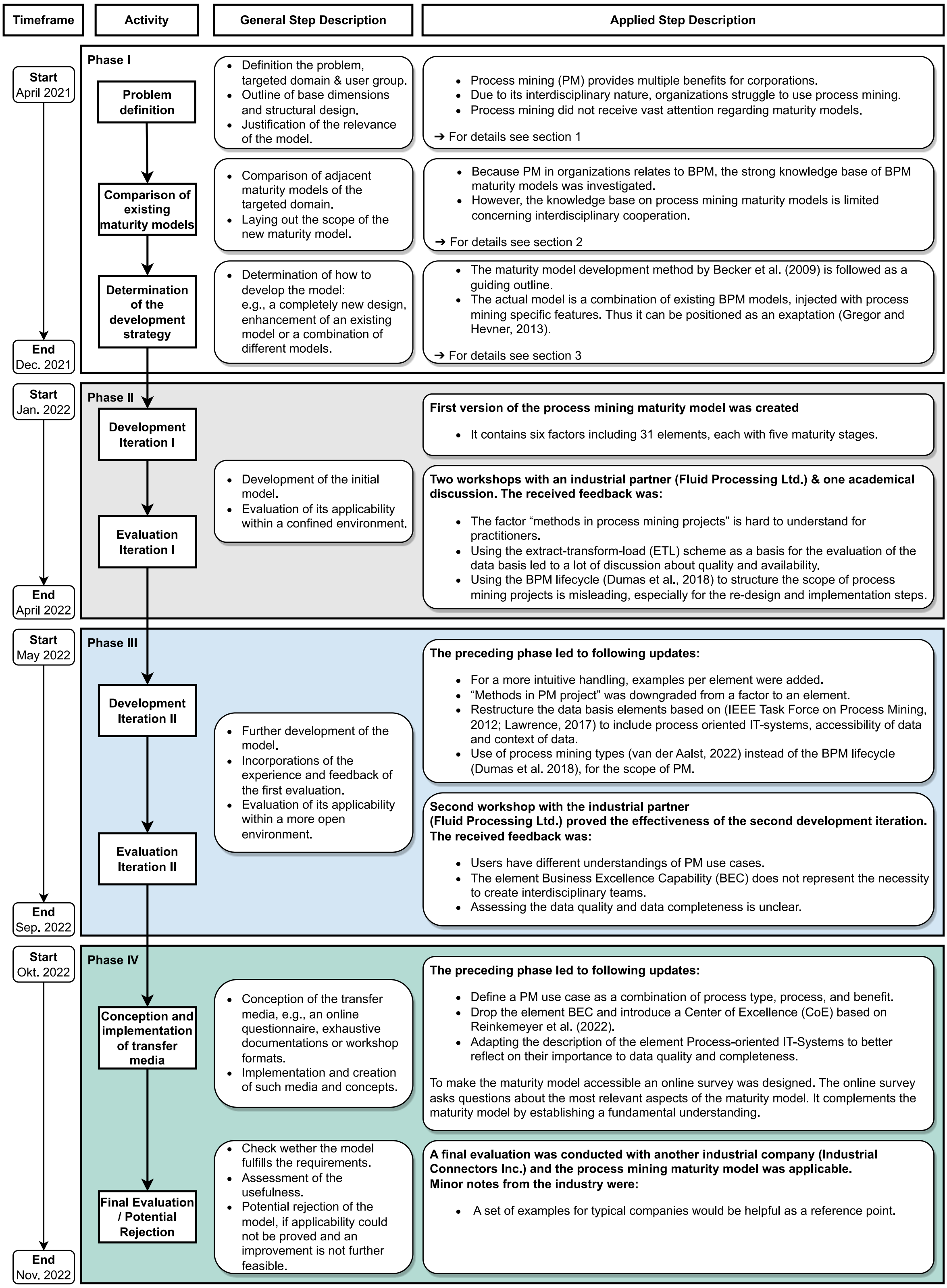

Figure 2. Applied Maturity Model Development Method (Adapted from Becker et al., 2009)

Multiple approaches for developing maturity models exist in the knowledge base (De Bruin et al., 2005; Mettler, 2010; Carvalho et al., 2019). Drawing on the Design Science Research paradigm (Hevner et al., 2004), Becker et al. (2009) provide a method for developing IT-related maturity models. Based on the properties and development history of preceding maturity models, Becker et al. (2009) created a holistic method that focuses on understandability and reproducibility of maturity models, while pursuing an iterative approach based on existing knowledge from the literature and 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 of technology. Thus, a frequent reconsideration is necessary to keep the model valid, up-to-date, and relevant. In order to assure further relevance and accessibility for the target audience, we consolidated Kühn et al. (2013) for certain design decisions, such as how to make the maturity model accessible.

We instantiate the method provided by Becker et al. (2009) in an 18-months endeavor starting in April 2021. We split the development into four phases, while beginning with the problem definition and the justification of the need for a process mining maturity model. By positioning it against existing maturity models within the BPM domain, the development strategy has been determined. Two research institutions and two companies were involved in the development. In total, eight people from academia, two business process managers and one data scientist from a manufacturing company named Fluid Processing Ltd., and two process and tool owners from the Industrial Connectors Inc. have been involved in the research process. Both involved organizations have not used process mining extensively in the past but are seasoned in using data-driven methods. The experience of the academics ranged from none to having applied process mining in several industrial cases, such covering multiple perspectives.

The Process Mining Maturity Model is an exaptation, which draws from the models in the BPM domain and transfers it to process mining (Gregor and Hevner, 2013). In the second phase, the first iteration of the maturity model was created accordingly. To ensure rigor and relevance, we worked with practitioners and additional academics (Hevner, 2007). In total, a requirement gathering phase, two development cycles and a final transitional phase have been performed with feedback from industry and academia. The last phase covers the development of the transfer media and the final evaluation of both the maturity model and the accompanying media.

4 Results

4.1 Development iterations of the process mining maturity model

Following the development strategy of exaptation, we designed an initial maturity model in the first development iteration based on a literature screening and various brainstorming sessions. The initial model contains six factors and 31 elements. Every element received a definition and five maturity stages based on CMM (see section 2.2). Although it was not originally planned to maintain exactly five maturity stages, this decision proved to be advantageous for two reasons. First, the practitioners were used to the concept of five maturity stages from various other models. Second, others also use the five-stage concept (e.g., the event log maturity stages (IEEE Task Force on Process Mining, 2012) or the Stanford Data Governance Model (Stanford DG, 2011). Figure 2 depicts the detailed development iterations II-IV. The first version included the six factors Organization, People, Governance, Methods in process mining project phases, Process Mining Application, and Data Availability. The first three factors Organization, People, and Governance together with their respective elements are based on the established BPM capabilities proposed and revisited in Rosemann and De Bruin (2005b, 2005a) and Kerpedzhiev et al. (2021), with Organization combining the Culture and Strategic Alignment core elements.

Within the Organization factor, the elements purpose (Reinkemeyer, 2020) and Business Excellence Capability were added. Business Excellence Capability was added to include the influence of already existing structures like BPM, Lean Management, or a Continuous Improvement Process (CIP). It was dropped in the final development iteration (Phase IV in Figure 2) in favor of a Center of excellence, as suggested by Reinkemeyer et al. (2022), because discussions with practitioners revealed that this form of organizational structure better reflects their needs.

The elements for the factor People are inspired by van der Aalst (2016), who introduces and covers various essentials about process mining and connects them to other relevant disciplines such as data mining to gain a holistic view. The factor Governance has not been changed throughout the development iterations.

The factor Methods in process mining project phases was originally included because Rosemann and De Bruin (2005b) also have a methods factor and multiple authors (van Eck et al., 2015; Emamjome et al., 2019) call for more methodological guidance in applying process mining. We observed that practitioners needed a lot of explanation for this factor. Consequently, we turned "Methods in process mining project phases" into an element within the Organization factor, so that is less complex.

The factor Process Mining Application was initially based on the BPM lifecycle proposed by Dumas et al. (2018), with the idea that process mining can support every lifecycle phase of BPM. However, in the very first evaluation phase (Phase II in Figure 2), discussions about the possibilities of applying process mining in the re-design and implementation phase showed that this approach was not feasible. Instead, the six process mining types proposed by van der Aalst (2022) were chosen. To further reflect that the factor process mining application aims to capture the capability of an organization to apply different process mining types to various processes, the name and maturity stage names were adapted.

Ultimately, the factor Data Availability received multiple adaptions. Originally stemming from the idea to depict how well an organization can extract, transform and load event logs, it was changed in the second development phase (Phase III in Figure 2) to cover the data readiness levels proposed by Lawrence (2017) in combination with the established event log maturity levels proposed in IEEE Task Force on Process Mining (2012). For that matter, the factor name was changed to Data Foundation.

4.2 Resulting Process Mining Maturity Model

The Process Mining Maturity Model consists of five factors that comprise 23 elements, each with five maturity stages, ranging from initial to optimizing. To reduce complexity in the model, the maturity model tries to follow a pattern across all maturity stages of the elements. The pattern is loosely based on the CMM maturity stages (see section 2.2), with added definitions for factors, elements, and levels to represent process mining maturity more accurately. The first and lowest stage "Initial" is used for not existing capabilities or undocumented guidelines. The second stage "Rudimentary" often describes a first contact through external personnel or untested practice. The third stage "Standalone" usually covers first pilot project by the organization itself. The fourth stage "Systematic" introduces repeatable structures as well as mechanisms to constantly evaluate and improve the maturity. The last stage "Optimizing" normally introduces long term visions and organizational structures, which are dedicated towards maintaining, improving, and strategically developing the maturity. Thereby, the highest achievable maturity is a form of self-optimization, where the organization becomes self-aware of improvement possibilities, is able to adjust to business needs and market changes, and has dedicated organizational entities working on process mining maturity aspects. For example, the highest maturity of the element data governance is a dedicated entity which bundles and develops data governance aspects and strategies. The entity's purpose is not to conduct process mining themself, but it rather functions as a supplier to other teams within the organization, based on the respective organization's needs. The terms coined for the three stages "Rudimentary," "Standalone," and "Optimizing" were chosen in line with the conventional naming of the CMM. To move up from one maturity stage to the next one, every stage below must be fulfilled (Rosemann and De Bruin, 2005a). Similar to the CMM, the maturity stages are of ordinal nature (Paulk et al., 1991). Therefore, the necessary effort varies in between elements and from level to level. An overview of the Process Mining Maturity Model with its factors and elements as well as their definitions can be found in Figure 3.

The first factor **Organization** combines aspects that describe how well the organization enables process mining. It consists of the six elements *Purpose, Center of excellence for process mining, Process centricity, Evidence centricity, Change centricity, and Methods of process mining project phases.* The elements *Process-, Evidence-, and Change-centricity* are adopted from Kerpedzhiev et al. (2021) and cover the mindset of an organization to think and work in processes, base their decisions on facts, and the openness to change their behavior, respectively. The elements do not improve process mining per se but are a vital foundation for any organization to thrive on process mining results. The element *Purpose* is based on Reinkemeyer (2020) and describes the proficiency of process mining use cases in organizations, as well as the long-term strategies, respectively. We define a process mining use case as the combination of a process mining type (e.g., process discovery, comparative process mining), a selected business process (e.g., order-to-cash, goods receiving), and a proposed business benefit (e.g., using the as-is process as an input for workshops or predicting lead times). Multiple use cases can be turned into a process mining vision, by developing a long-term strategy of what value process mining should bring to the organization (e.g., in the form of a roadmap) and the definition of performance indicators that supervise the alignment. The element *Center of excellence* is based on findings and suggestions by Reinkemeyer et al. (2022) that companies with a dedicated team of interdisciplinary people are crucial for establishing and developing process mining competencies. The last element is *Methods of process mining project phases.* As various authors (van Eck et al., 2015; Emamjome et al., 2019) call for more guidance in the practical application of process mining, this element captures an organizational capability to use and maintain methodological guidance for their process mining efforts.

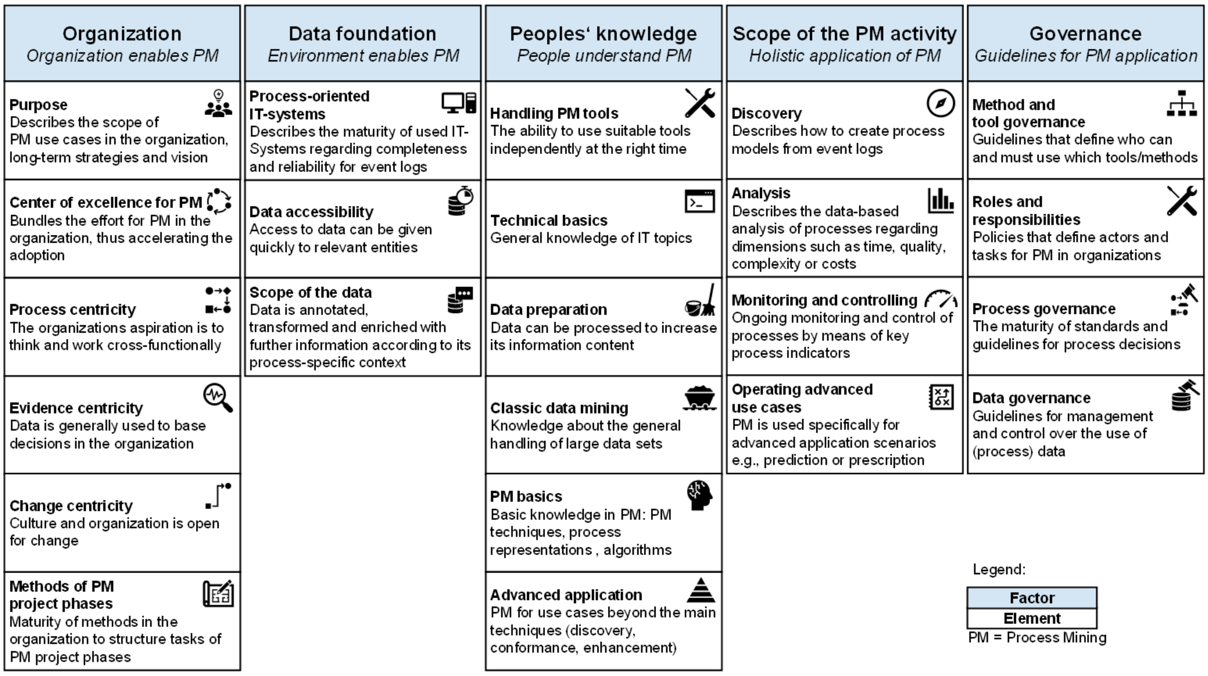

Figure 3 Overview of the Process Mining Maturity Model with the model's factors and elements[1]

The second factor **Data foundation** contains the three elements *Process-oriented IT-systems, Data accessibility, and Scope of the data*. The idea is to rate the underlying IT and data environment for process mining efforts, instead of the quality of event logs that have been exported before. Therefore, the element *Process-oriented IT-systems* is based on the maturity levels for event logs, particularly focusing on the provided examples to ensure applicability (IEEE Task Force on Process Mining, 2012). An increased maturity in this element leads to processes that are completely covered by IT-systems with a high quality of the data. Supplementary, *Data accessibility,* and *Scope of data* cover how quickly data can be retrieved from the environment and how much context in the form of meta data, additional attributes or additional information is given. These two elements are included based on Lawrence (2017)

[1] 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/

because speed and context increase the possibility of creating high quality process mining results. The factor Data Foundation does not dictate how exactly companies can improve the respective element exactly. In this way, organizations can draw from latest developments in the field of IT-infrastructure and data tools.

The third factor **Peoples' knowledge** describes peoples' knowledge on process mining within the organization. The factor combines the six elements *Handling process mining tools, Technical basics, Data preparation, Classic data mining, Process mining basics, and Advanced application* which are all mentioned in van der Aalst (2016). The general idea of this factor is that process mining can require a diverse knowledge base with topics from machine learning, being able to use tools properly, handling data or process mining specific algorithms, challenges, and pitfalls.

The fourth factor **Scope of the process mining activity** covers which process mining types are applied in which intensity (i.e., how many use cases / processes are covered). The elements *Discovery, Analysis, Monitoring and controlling,* and *Operating advanced use cases* are based on the six types of process mining which are introduced in van der Aalst (2022), with the latter one combining comparative, predictive, and action-oriented process mining. The factor with its elements is used in this maturity model to display the diverse possibilities of applying process mining. Furthermore, it enables organizations to set a focus on certain types of process mining.

The last factor **Governance** contains the four governing elements *Method and tool, Roles and responsibilities, Process-,* and *Data governance*. Maintaining large scale process mining efforts requires certain regulatory rules and guidelines. It is mainly adopted from De Bruin and Rosemann (2007) and Kerpedzhiev et al. (2021), with an addition of Data governance based on IBM (2007) and Stanford DG (2011). The Governance structures define the tools used, who is accountable and responsible for certain tasks, and who is allowed to access, change, and update processes and data.

4.3 Demonstration of the Process Mining Maturity Model

The Process Mining Maturity Model was applied to an organization from the industrial connectors business (Industrial Connectors Inc.) with around 7,000 employees worldwide. To provide an easier introduction to the detailed maturity model, a short online survey was used. The online survey contained questions on the most relevant aspects of the Process Mining Maturity Model. This includes the motivation, the status of process mining projects and use cases, the experience in exporting data, and whether process mining tools are available. By analyzing the online survey, the workshop in which the complete Process Mining Maturity Model is assessed was prepared. The workshop was held with two process and tool owners from the Industrial Connectors Inc., who are responsible for the product lifecycle management (PLM). In the workshop, all 23 elements were discussed and assessed. After rating the as-is maturity, the participants set the to-be maturity for certain elements. The rated maturity model for Industrial Connectors Inc. is displayed in Figure 4. The textual descriptions next to the maturity stages are the default texts for the respective as-is maturity stage.

The as-is maturity is indicated by the gray levels in Figure 4. The rating by Industrial Connectors Inc. showcases that the organization established professional process management structures. This is evident in the assessment of the elements Process centricity, Process-oriented IT-systems, and Process governance with the highest maturity stage "Optimizing". The company is continuously working on their end-to-end business processes with dedicated teams to optimize them, based on defined rules and roles on how to change business processes. For that matter, workflow-oriented PLM-systems have been established in the past years. In the workflows, all subsidiaries worldwide run the same processes. However, the process owners only recently discovered process mining. Inevitably, the assessments for process mining related capabilities are lower. This becomes especially evident for the organization factor with a "Rudimentary" rating for the elements Purpose and Center of excellence for process mining. While the company does have a starter process mining use case defined, they have been working on the establishment of the technology without a cross-divisional team and they have not applied process mining themselves yet (only through third parties). Consequently, they have not been able to establish knowledge about process mining tools and techniques within the company. This is evident in the factor

Peoples' knowledge with a low maturity in the elements of Handling process mining tools ("Rudimentary"), Classic data mining ("Rudimentary") or Process mining basics ("Rudimentary"). Furthermore, every element in the factor Scope of the process mining activity (which indicates how many process mining techniques are applied to a larger number of processes / use cases) is rated at the maturity stage two ("Rudimentary").

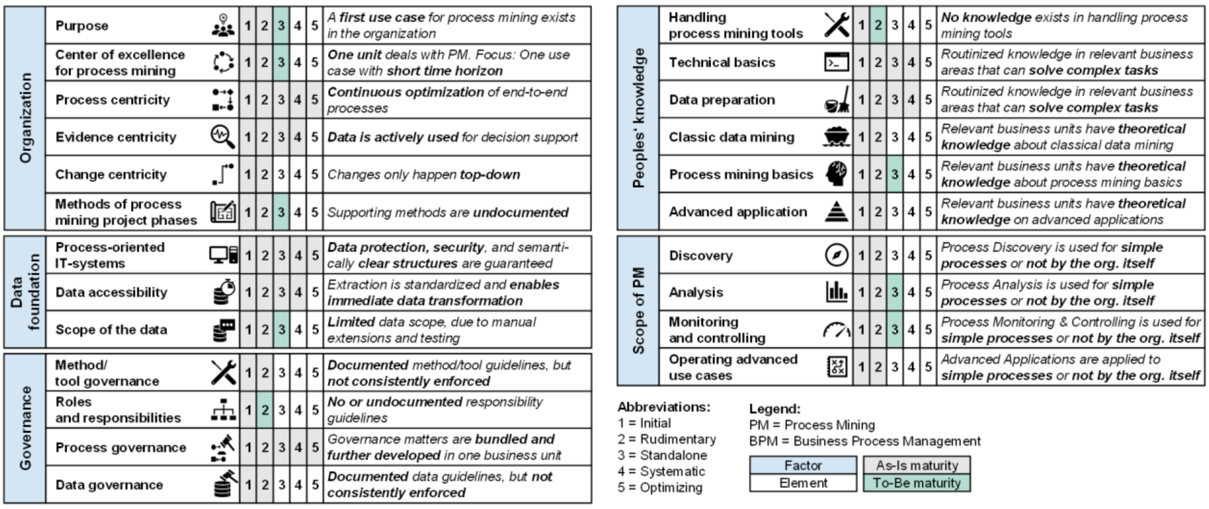

Figure 4 Applied maturity model for Industrial Connectors Inc.

Based on the as-is assessment, a to-be prescription was conducted. The to-be maturity is indicated by the green levels in Figure 4. The two process owners used the various elements to reflect and prioritize how to improve their overall maturity. The company is planning to establish more process mining projects and knowledge within their organization. In a follow-up workshop, actions are derived to meet these to-be maturity stages. For the Purpose element, this means that the first use cases need to be transformed into a long-term vision, supported by indicators to measure, and monitor the vision's and use case's success. Simultaneously, an interdisciplinary team that addresses multiple use cases needs to be established, combining various departments such as IT and PLM. The interdisciplinary team will set its Scope of process mining activity on more use cases for the analysis and monitoring aspects of process mining, which is represented by the "Standalone" maturity for the elements Analysis and Monitoring and controlling. Accordingly, the team will need to be able to operate process mining tools on their own, which is represented by the "Standalone" maturity rating for the element Handling process mining tools.

Various best practices have been identified while applying the maturity model. First, an application procedure has been derived. The application procedure is depicted in Figure 5. Second, a regularly discussed aspect is how to improve the quality of process mining results in contrast to improving the quantity. For that matter, the two factors Peoples' knowledge and Scope of process mining activity are important. An educated team can produce more reliable and useful process mining results for the organization, without changing the input, hence increasing the quality of results. For example, by increasing knowledge in the element Data preparation, raw event data can be feature engineered to receive much better results. In contrast, the factor Scope of the process mining activity covers the different process mining types as elements, with the maturity stages being mostly an expansion to different processes / more use cases. This results in a quantitative increase in types as well as processes. Third, another best practice is understanding the Process Mining Maturity Model not as a benchmark, but rather as a tool to (re-)focus the organizational activities. It is not worth assessing an organization to the highest maturity stage for every element. Instead, critically questioning whether the current activities provide the opportunity to flourish as an organization. Additionally, if there is doubt about the exact maturity stage, the practitioners should question whether the element is something they should work on (hence assessing themselves on a lower stage) or whether they are satisfied with the status quo (assessing themselves on a higher stage). Fourth, along the path of maturing process mining activities in organizations, there may be different goals, starting conditions, circumstances, and paths in general. Organizations are best advised to use the maturity model as a tool to prioritize their work and improve their process mining activities holistically and sustainably.

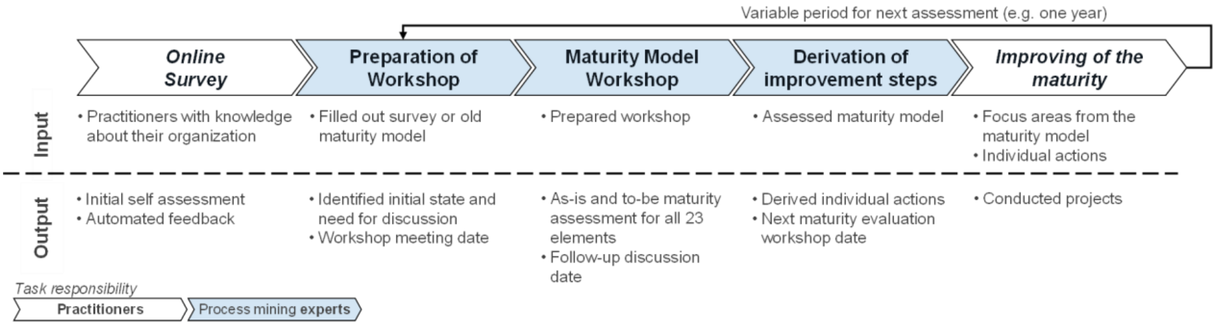

Figure 5 Derived application procedure of the maturity model

5 Discussion

Assessing process mining activities in organizations

Process mining allows organizations to gain transparency over their business processes, enabling them to monitor and improve them based on data. Various aspects impact the success of process mining activities. However, organizations struggle with assessing their process mining activities due to a lack of proper maturity models that cover all of the influencing aspects, as well as a lack of methods and tools to apply such models. On the one hand, previous publications on BPM maturity models such as the BPMMM (Rosemann and De Bruin, 2005b) or PEMM (Hammer, 2007) do not consider the data or technical requirements needed to establish process mining capabilities. On the other hand, process mining maturity models such as Jacobi et al. (2020) or Linden (2021) do not comprise multiple factors with precise maturity stages that enable organizations to derive meaningful actions.

In this paper, we design a multi-factor Process Mining Maturity Model. The model contains five factors with a total of 23 elements, with five distinct maturity stages each. From a scientific perspective, we contribute by the exaptation of existing models. The maturity stages are based on the established levels in CMM (Paulk et al., 1991). These maturity stages were adapted to reflect the organizational embedding better (e.g., the third stage is not “Defined” but rather “Standalone”). For the factors and elements, the BPM capability framework proposed by Rosemann and De Bruin (2005b) and Kerpedzhiev et al. (2021) is taken as a foundation. This is reflected in elements like the Process-, Evidence-, and Change-centricity within the factor Organization, as well as in the elements Process- and Data Governance in the factor Governance. Because process mining is interdisciplinary, these BPM related aspects are expanded by data maturity levels, such as the maturity level for event logs or the data readiness model (IEEE Task Force on Process Mining, 2012; Lawrence, 2017). Additionally, the required knowledge (i.e., people’s capabilities regarding tools, data, and process mining), the scope of process mining (i.e., the process mining types used in different processes / use cases) and the required organizational structures (i.e., the establishment of a center of excellence) are explicitly considered based on van der Aalst (2016, 2022) and Reinkemeyer et al. (2022), respectively. By aggregating all these different aspects, we contribute a comprehensive Process Mining Maturity Model to the knowledge base. Furthermore, we demonstrate its application at Industrial Connectors Inc. and asses the current as-is maturity through an online survey that proved to be an easy entry point for the complete maturity model. Hence, we meet the requirement of an easy application postulated by Becker et al. (2009) and Kühn et al. (2013).

Improving process mining activities in organizations

Based on the assessment results that indicate a current maturity stage, organizations aim to derive actions to improve their process mining readiness. Mans et al. (2013) and Mamudu et al. (2022) provide valuable insight into process mining success factors. They show that process mining success is not only depending on technical expertise but also on aspects like information availability, education, and management support. Our model provides organizations with the means to derive actions for improvement based on a to-be assessment. By applying the maturity model and demonstrating its applicability, we ensure ease of use and understandability, following instructions for the validation of maturity models' accessibility by Becker et al. (2009) and Kühn et al. (2013). However, regarding the classification of maturity models into descriptive, prescriptive, and comparative according to De Bruin et al. (2005), we only provide a descriptive model. A prescriptive model would require desirable to-be maturity levels or meaningful approaches to reach these to-be levels. While the organizations can set a focus with their to-be assessment, it is mostly an individual task to derive concrete actions from the identified focus areas. There is no possibility to validate whether the to-be maturity levels are desirable. Neither are concrete actions associated with the increase of one maturity level to the next one available.

The application of our maturity model guides organizations in establishing process mining capabilities relevant to their respective organizational needs. The improvement of process mining capabilities in turn leads to improved process mining results, concerning both efficiency and effectiveness.

6 Conclusion & Outlook

Organizations have addressed their business processes differently in the past by implementing initiatives like Lean Management, Business Process Reengineering, or BPM. Process mining only recently emerged as a research discipline (van der Aalst, 2022). The techniques and tools can be expected to further mature in the upcoming years, and how organizations exactly utilize process mining to their advantage is still to be defined (Badakhshan et al., 2023). Consequently, factors, elements, and maturity stages need to be continuously reviewed, and their relevance for organizations validated (Hevner, 2007).

In this paper, we design a multi-factor Process Mining Maturity Model. The model is an exaptation from established capability model and areas from the BPM discipline, data science, and process mining. It contains five factors with a total of 23 elements, each with five distinct maturity stages. We prove the usefulness of the maturity model by applying it to the Industrial Connectors Inc. and demonstrate an application procedure to derive focus areas and actions for improvement for organizations.

Naturally, the results are subject to limitations. While we developed and applied the maturity model with two companies, employing the model in different organizations or domains might lead to a refinement of the model. Hence, future research can detail and refine our model, for example by developing detailed guidelines that prescribe steps to achieve higher maturity stages. As suggested by Becker et al. (2009), a large database of the model's applications could be used to quantify and adjust the model. 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. To make this long-term development more intuitive, as well as increase the comparability, future research could also focus on identifying the weighted relevance of every element, such that aggregated maturity levels can be calculated.

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References

Badakhshan, P., Wurm, B., Grisold, T., Geyer-Klingeberg, J., Mendling, J. and vom Brocke, J. (2023). "Creating Business Value with Process Mining." in: *Journal of Strategic Information Systems (JSIS)*.

Becker, J., Knackstedt, R. and Pöppelbuß, J. (2009). "Developing Maturity Models for IT Management: A Procedure Model and its Application." *Business & Information Systems Engineering*, *1*(3), 213–222.

Beverungen, D., Buijs, J. C. A. M., Becker, J., Di Ciccio, C., van der Aalst, W. M. P., Bartelheimer, C., vom Brocke, J., Comuzzi, M., Kraume, K., Leopold, H., Matzner, M., Mendling, J., Ogonek, N., Post, T., Resinas, M., Revoredo, K., del-Río-Ortega, A., La Rosa, M., Santoro, F. M., Solti, A., Song, M., Stein, A., Stierle, M. and Wolf, V. (2021). "Seven Paradoxes of Business Process Management in a Hyper-Connected World." *Business & Information Systems Engineering*, *63*(2), 145–156.

Carvalho, J. V., Pereira, R. H. and Rocha, Á. (2019). "Development Methodology of a Higher Education Institutions Maturity Model." in: F. Xhafa, L. Barolli, & M. Greguš (Eds.), *Advances in Intelligent Networking and Collaborative Systems* (Vol. 23, pp. 262–272). Cham: Springer International Publishing.

CMMI Product Team. (2010). "CMMI for Development, Version 1.3."

De Bruin, T. and Rosemann, M. (2007). "Using the Delphi Technique to identify BPM Capability Areas." *ACIS 2007 Proceedings*, *42*.

De Bruin, T., Rosemann, M., Freeze, R. and Kaulkarni, U. (2005). "Understanding the Main Phases of Developing a Maturity Assessment Model." in: D. Bunker, B. Campbell, & J. Underwood (Eds.), *Australasian Conference on Information Systems (ACIS)* (pp. 8–19).

Dumas, M., La Rosa, M., Mendling, J. and Reijers, H. A. (2018). *Fundamentals of Business Process Management*. Berlin, Heidelberg: Springer Berlin Heidelberg.

Dunzer, S., Zilker, S., Marx, E., Grundler, V. and Matzner, M. (2021). "The Status Quo of Process Mining in the Industrial Sector." in: F. Ahlemann, R. Schütte, & S. Stieglitz (Eds.), *Innovation Through Information Systems* (pp. 629–644). Cham: Springer International Publishing.

Emamjome, F., Andrews, R. and ter Hofstede, A. H. M. (2019). "A Case Study Lens on Process Mining in Practice." in: H. Panetto, C. Debruyne, M. Hepp, D. Lewis, C. A. Ardagna, & R. Meersman (Eds.), *On the Move to Meaningful Internet Systems: OTM 2019 Conferences* (Vol. 11877, pp. 127–145). Cham: Springer International Publishing.

Felch, V. and Asdecker, B. (2020). "Quo Vadis, Business Process Maturity Model? Learning from the Past to Envision the Future." in: D. Fahland, C. Ghidini, J. Becker, & M. Dumas (Eds.), *Business Process Management* (Vol. 12168, pp. 368–383). Cham: Springer International Publishing.

Gausemeier, J., Bensiek, T., Kühn, A. and Grafe, M. (2012). "MATURITY BASED IMPROVEMENT OF PRODUCT DEVELOPMENT PROCESSES IN SMALL AND MEDIUM-SIZED ENTERPRISES." in: *DS 70: Proceedings of DESIGN 2012, the 12th International Design Conference, Dubrovnik, Croatia* (pp. 41–50).

Gregor, S. and Hevner, A. R. (2013). "Positioning and Presenting Design Science Research for Maximum Impact." *MIS Quarterly*, *37*(2), 337–355.

Hammer, M. (2007, April 1). "The Process Audit." *Harvard Business Review*.

Hevner, A. R. (2007). "A Three Cycle View of Design Science Research." *Scandinavian Journal of Information Systems*, *19*(2).

Hevner, A. R., March, S. T., Park, J. and Ram, S. (2004). "Design Science in Information Systems Research." *MIS Quarterly*, *28*(1), 75–105.

IBM. (2007, October). "The IBM Data Governance Council Maturity Model: Building a roadmap for effective data governance."

IEEE Task Force on Process Mining. (2012). "Process Mining Manifesto." in: F. Daniel, K. Barkaoui, & S. Dustdar (Eds.), *Business Process Management Workshops* (Vol. 99, pp. 169–194). Berlin, Heidelberg: Springer Berlin Heidelberg.

Jacobi, C., Herborn, Lutz, Furmans, Kai, and Mathias Meier. (2020). "Maturity Model for Applying Process Mining in Supply Chains: Literature Overview and Practical Implications." *Volume 2020*, Issue 12.

Kerpedzhiev, G. D., König, U. M., Röglinger, M. and Rosemann, M. (2021). "An Exploration into Future Business Process Management Capabilities in View of Digitalization." *Business & Information Systems Engineering*, *63*(2), 83–96.

Kipping, G., Djurica, D., Franzoi, S., Grisold, T., Marcus, L., Schmid, S., Brocke, J. vom, Mendling, J. and Röglinger, M. (2022). "How to Leverage Process Mining in Organizations - Towards Process Mining Capabilities." in: C. Di Ciccio, R. Dijkman, A. del Río Ortega, & S. Rinderle-Ma (Eds.), *Business Process Management* (pp. 40–46). Cham: Springer International Publishing.

Kühn, A., Bensiek, T. and Gausemeier, J. (2013). "Framework for the development of maturity based self-assessments for process improvement." in: *ICED13. Proceedings of the 19th International Conference on Engineering Design. Volume 1: Design processes* (pp. 119–128).

Lawrence, N. D. (2017). "Data Readiness Levels." arXiv.

Linden, E.-J. van der. (2021). *Successful Process Improvement: A Practice-Based Method To Embed Process Mining In Enterprises* (1st ed.). Tilia Cordata IT B.V.

Mamudu, A., Bandara, W., Wynn, M. T. and Leemans, S. J. J. (2022). "A Process Mining Success Factors Model." in: C. Di Ciccio, R. Dijkman, A. del Río Ortega, & S. Rinderle-Ma (Eds.), *Business Process Management* (Vol. 13420, pp. 143–160). Cham: Springer International Publishing.

Mans, R., Reijers, H., Berends, H., Bandara, W. and Rogier, P. (2013). "Business process mining success." in: *ECIS 2013 Completed Research*.

Marquez-Chamorro, A. E., Resinas, M. and Ruiz-Cortes, A. (2018). "Predictive Monitoring of Business Processes: A Survey." *IEEE Transactions on Services Computing*, *11*(6), 962–977.

Martin, N., Fischer, D. A., Kerpedzhiev, G. D., Goel, K., Leemans, S. J. J., Röglinger, M., van der Aalst, W. M. P., Dumas, M., La Rosa, M. and Wynn, M. T. (2021). "Opportunities and Challenges for Process Mining in Organizations: Results of a Delphi Study." *Business & Information Systems Engineering*, *63*(5), 511–527.

Mettler, T. (2010). "Thinking in Terms of Design Decisions When Developing Maturity Models:" *International Journal of Strategic Decision Sciences*, *1*(4), 76–87.

Niewöhner, N., Lang, N., Asmar, L., Röltgen, D., Kühn, A. and Dumitrescu, R. (2021). "Towards an ambidextrous innovation management maturity model." *Procedia CIRP*, *100*, 289–294.

Paulk, M. C., Curtis, B. and Chrissis, M. B. (1991). *Capability Maturity Model for Software,*. CARNEGIE-MELLON UNIV PITTSBURGH PA SOFTWARE ENGINEERING INST. URL: https://apps.dtic.mil/sti/citations/ADA240603 (visited on September 6, 2022)

Paulk, M. C., Curtis, B., Chrissis, M. B. and Weber, C. V. (1993). "Capability maturity model, version 1.1." *IEEE Software*, *10*(4), 18–27.

Pentland, B. T., Liu, P., Kremser, W. and Haerem, T. (2020). "The Dynamics of Drift in Digitized Processes." *MIS Quarterly*, *44*(1), 19–47.

Reinkemeyer, L. (Ed.). (2020). *Process Mining in Action: Principles, Use Cases and Outlook*. Cham: Springer International Publishing.

Reinkemeyer, L., Grindemann, P., Egli, V., Röglinger, M., Marcus, L. and Fabri, L. (2022). "Accelerating Business Transformation with a Process Mining Center of Excellence (CoE)." URL: https://www.celonis.com/report/fraunhofer-study/ (visited on September 28, 2022)

Röglinger, M., Plattfaut, R., Borghoff, V., Kerpedzhiev, G., Becker, J., Beverungen, D., vom Brocke, J., Van Looy, A., del-Río-Ortega, A., Rinderle-Ma, S., Rosemann, M., Santoro, F. M. and Trkman, P. (2022). "Exogenous Shocks and Business Process Management: A Scholars' Perspective on Challenges and Opportunities." *Business & Information Systems Engineering*, *64*(5), 669–687.

Röglinger, M., Pöppelbuß, J. and Becker, J. (2012). "Maturity models in business process management." *Business Process Management Journal*, *18*(2), 328–346.

Rosemann, M. and De Bruin, T. (2005a). "Application of a Holistic Model for Determining BPM Maturity," *BP Trends, 2*, 1–21.

Rosemann, M. and De Bruin, T. (2005b). "Towards a Business Process Management Maturity Model." in: F. Rajola, D. Avison, R. Winter, J. Becker, P. Ein-Dor, D. Bartmann, F. Bodendorf, C. Weinhardt, & J. Kallinikos (Eds.), *ECIS 2005* (pp. 1–12).

SEI Carnegie Mellon University. (2009). "CMMI: A Short History." URL: https://resources.sei.cmu.edu/library/asset-view.cfm?assetid=28414 (visited on September 7, 2022)

Stanford DG. (2011, October 17). "Data Government at Stanford."

Tarhan, A., Turetken, O. and Reijers, H. A. (2016). "Business process maturity models: A systematic literature review." *Information and Software Technology*, *75*, 122–134.

van der Aalst, W. M. P. (2016). *Process Mining - Data Science in Action*. Berlin, Heidelberg: Springer Berlin Heidelberg.

van der Aalst, W. M. P. (2022). "Process Mining: A 360 Degree Overview." in: W. M. P. van der Aalst & J. Carmona (Eds.), *Process Mining Handbook* (Vol. 448, pp. 3–34). Cham: Springer International Publishing.

van der Aalst, W. M. P. and Carmona, J. (Eds.). (2022). *Process Mining Handbook* (Vol. 448). Cham: Springer International Publishing.

van Eck, M. L., Lu, X., Leemans, S. J. J. and van der Aalst, W. M. P. (2015). "PM^2: A Process Mining Project Methodology." in: J. Zdravkovic, M. Kirikova, & P. Johannesson (Eds.), *Advanced Information Systems Engineering* (Vol. 9097, pp. 297–313). Cham: Springer International Publishing.

Weinzierl, S., Dunzer, S., Zilker, S. and Matzner, M. (2020). "Prescriptive Business Process Monitoring for Recommending Next Best Actions." in: D. Fahland, C. Ghidini, J. Becker, & M. Dumas (Eds.), *Business Process Management Forum* (Vol. 392, pp. 193–209). Cham: Springer International Publishing.

zur Heiden, P. and Beverungen, D. (2022). "A Renaissance of Context in Design Science Research." Presented at the Hawaii International Conference on System Sciences.