Towards a Maturity Model of Process Mining as an Analytic Capability

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Abstract

Process mining applications offer a range of capabilities to analyze processes and improve organizational performance. Evaluating process mining capabilities is essential to demonstrate the business value created by process mining. Currently, there is a paucity of studies to evaluate the maturity of process mining analytic capability. This paper aims to close this gap. We created the first version of a maturity model of process mining as an analytical capability integrating the maturity models available for business process management, data analytics, and Artificial Intelligence (AI) organizational capabilities. Then, we evaluated the model with qualitative interviews with process mining experts. The interview feedback has been used to design an improved version of the proposed maturity model, which we aim to deploy in real-world case studies in the future.

Keywords: maturity model, process mining, analytic capability

1. Introduction

Process mining (PM) has recently gained extensive traction in the industry. The staggering growth of the process mining market is mainly driven by the value increase of PM technology, i.e., the tools that enable process mining analysis. Organizations, however, struggle on a daily basis to design, implement and monitor their process mining initiatives (Eggers et al., 2021) and, more generally, face the challenge of how to extract value continuously from them (Martin et al., 2021).

The challenges of setting up and running a PM initiative range from understanding the technology (Martin et al., 2021), e.g., the input data required and the type of insights that it could potentially yield, to creating a supportive organizational environment in which appropriate tools and skills are available (Badakhshan et al., 2022). These challenges relate to transforming PM from a promising technology that is nowadays widely available in the market to an organizational *capability* that creates value for a company and its customers on a continuous basis. PM can, in fact, be perceived as an analytic capability of organizations: it enables the analysis of the data generated by the execution of business processes to gain insights into the ways in which they can be made more effective and efficient (Badakhshan et al., 2022; Pfahlsberger et al., 2021). Recent studies have tried to analyze the critical success factors of process mining (Mamudu et al., 2023) and the challenges of leveraging process mining in organizations (Kipping et al., 2022). These approaches, however, take a static perspective, failing to provide guidance to organizations to *improve* in their process mining implementation and exploitation journey.

Maturity models can guide with respect to the development of analytic capabilities. Capability maturity models are conceptual multistage models that describe typical patterns in developing organizational capabilities. They have emerged as a widely used class of tools that help organizations understand how to implement and/or appropriate the value of relatively new technology or capabilities (Hüner et al., 2009; Martin et al., 2021). A maturity model identifies the dimensions in which capabilities are relevant and an assessment model. The maturity of a capability in a dimension is usually assessed along five possible levels of maturity, from initial/ad hoc, when an organization is starting to realise the existence and potential of a capability, to optimizing, when a capability is widely available in the organization, effectively managed, and periodically reviewed for improvement. While such a level-based view on maturity has been recently criticised as not capturing the actual difficulty for an organization to

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improve from one level to the next one (Tarhan et al., 2016), it is still widely adopted.

Many maturity models have been proposed in the literature focusing on the business process management (BPM) capability (Van Looy et al., 2014; Van Looy et al., 2017) and (AI-enabled) data analytic organizational capabilities (e.g., Korsten et al., 2022; Zebec and Indihar Štemberger, 2020). Both types of maturity models fail short when considering PM. On the one hand, BPM maturity models see PM only as a technological sub-dimension that can help organizations achieve a more data-driven focus in a BPM initiative. On the other hand, data analytics and AI maturity models fail to capture the specificity of PM, particularly from the technological standpoint, e.g., the type of data required by PM and the functionality that PM offers its users. Based on these premises, the research question we face is: *How can we design a maturity model of PM as an organizational analytic capability?*

To answer this question, we present the development of P3M (Process Mining Maturity Model) in this paper, for which we followed a design science research (DSR) approach. This paper represents the first cycle of the approach and is mixed with the other method. First, we have identified the existing maturity models on BPM, data analytics, and AI in organizations in the literature to understand how to characterize PM as an analytic capability. Then, we designed an initial version (α-P3M) of the maturity model based on the findings from the literature review. Through interviews with five PM experts, a new and improved version (β-P3M) of the maturity model was obtained.

The remainder of this paper is structured as follows. Section 2 discusses the related work, while Section 3 describes the research methodology. Section 4 and Section 5 present the results of our research, i.e., α-P3M and β-P3M, respectively. The conclusions are drawn in Section 6.

2. Background and Related Work

Process mining is constantly evolving, with significant improvements expected to enhance its impact (Accorsi and Lebherz, 2022), including the adoption of modular, analytical architectures for easy data extraction and transformation, the maturation of data connectors for better compatibility across vendors, and data model advancements enabling end-users to shift between case perspectives, reducing the reliance on single case types.

Meanwhile, AI-enabled Process Mining is also emerging. It comprises four levels: descriptive, diagnostic, predictive, and prescriptive(Lehto, 2021; Veit et al., 2017). Descriptive process mining uses statistical analysis and machine learning techniques to understand past events, identify process variations, and anomalies. Diagnostic mining employs machine learning to classify problems and discern process changes over time, facilitating identification of issues and corrective actions. Predictive mining uses historical data to forecast process outcomes and other aspects of interests. Finally, prescriptive mining offers optimization insights, cost reduction strategies, and customer satisfaction improvement measures, by identifying improvement areas and suggesting specific actions (Dumas et al., 2023).

Maturity models, according to Becker et al. (2009) and Tarhan et al. (2016), present a structured series of levels for a specific organizational capability within a business domain. This model elucidates the progression of a capability towards greater maturity, allowing organizations to evaluate their current state, identify areas for improvement, and monitor progress during implementation.

Various researchers have explored and critically examined the use of maturity models in BPM (Dumas et al., 2018; Fisher, 2004; Froger et al., 2019; Rohloff, 2009; Weber et al., 2008). De Bruin et al. (2005) identified six factors critical to an organization's BPM capabilities: Information Technology and Systems, Culture, Methodology, Strategic Alignment, People, and Governance. Van Looy et al. (2017) evaluated the BPM Maturity Model (BPMM) utilizing samples from various maturity models, considering competencies such as modeling, deployment, optimization, management, culture, and structure. Note that most maturity models proposed for BPM do not explicitly mention process mining as a capability, and see process mining at most as a potential area to explore.

The field of process mining maturity models is still nascent. Jacobi et al. (2020) developed a maturity model for process mining in a supply chain cross-organizational context, classifying 34 papers into a three-stage maturity model. Brock et al. (2023) recently proposed a process mining maturity model based on five factors and 23 elements, focusing solely on the organizational aspects of process mining initiatives without specifically addressing the technological scope of process mining. There is potential to build upon this model by integrating technological aspects and other capabilities.

Other approaches see the maturity of process mining principally in the other fields, focusing on AI and data analytics maturity models. Akkiraju et al. (2020), Chen et al. (2022), Pringle and Zoller (2018), Saari et al. (2019), Schreckenberg and Moroff (2021), and Vaish et al. (2021) proposes AI maturity models that integrated into enterprise architecture. Similarly, Korsten et al. (2022) assesses the contribution of data analytics maturity to business value. Both AI and data analytics can be amalgamated to enhance process mining functionality (Dumas et al., 2023). In this context, the technology dimension is extended beyond the mere availability of data for BPM. It also necessitates an examination of how data is acquired, processed, and disseminated, along with pertinent issues related to its security and governing policies.

The modelling of the process mining capabilities also should consider the process mining success factors identified by Mamudu et al. (2023). These include change management, tool capabilities, training, structured approaches, data quality, project management, stakeholder support, information availability, and technical expertise. Process mining also have to create value through end-to-end process visualization, performance indicators, sense-making of process-related information, data-driven decision-making, and implementation of interventions, thereby enhancing organizational efficiency and decision-making capabilities (Badakhshan et al. (2022)).

3. Methodology

The methodology that we adopted for the development of this research is sketched in Fig. 1. We follow the framework of De Bruin et al. (2005), which defines six phases to develop and manage a maturity model: scope, design, populate, test, deploy, and maintain. This paper focuses specifically on the development (i.e., scoping, designing, populating, and testing) of P3M. This paper is in fact the first step of a broader research scope, in which we plan also to deploy and maintain P3M as a tool that can be used in practical case studies. We draw the suggestion of iterating through different versions of P3M from Becker et al. (2009).

The four phases identified by De Bruin et al. (2005) that we cover in this paper are described next.

Scope. The first phase is developing the scope of the desired model. Here the focus of the model and the stakeholders that it targets are defined.

Design. The next step involves creating a model blueprint. This requires defining terms such as audience, method of application, driver of the application, respondent, and application. There are

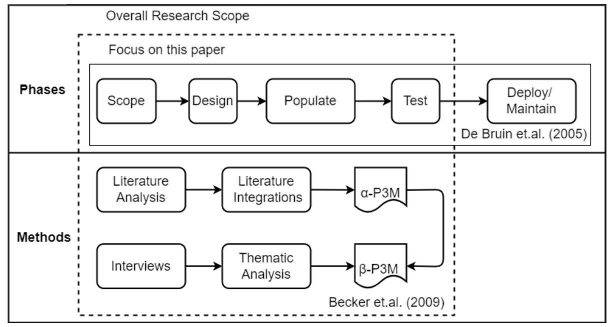

Figure 1. Research Methodology: Phases and Methods

two approaches to defining maturity stages: top-down and bottom-up. The former starts with definitions then develops measures, suitable for less mature domains, while the latter determines measures first then forms definitions, effective for more mature domains (De Bruin et al., 2005). As this is the inaugural effort to create a PM maturity model, we chose a top-down approach, defining the maturity model first, followed by developing measures for the maturity levels.

Populate. After defining the scope and the design of the model, the focus shifts to deciding what content should be included. This involves identifying the aspects (dimensions) that need to be measured in the maturity assessment and determining the methods for measurement. For the development of α-P3M, we relied on an analysis of the literature and compared existing maturity models that had an intersection with the process mining maturity model domain.

Test. Once a model has been created, it is necessary to evaluate its accuracy and relevance. This involves testing both the constructs of the model and the model instruments for validity, reliability, and generalizability. In this research, for the testing of α-PM3 and the subsequent development of its second version (β-P3M), we relied on interviews with domain experts, followed by a thematic analysis to elicit the dominant common themes from the interviews that could help us improving the maturity model.

We approached six industry experts in process mining from various organizations worldwide whose background represents various stakeholders of the maturity model, such as practitioners and consulting companies. Tab. 1 presents an overview of the interviewed participants. The experts belong to large-sized organizations that have been utilizing process mining for over a year and view it as a crucial technology for generating business value. Note that the interview with expert A was used as a pilot to fine tune the interview material.

We used a semi-structured interview guideline,[1] which included:

- Two mock-up case studies demonstrating the application of the α-P3M within two organizations exhibiting different maturity levels. One case study reflects an organization's infancy stage, while the other depicts a more advanced organization using process mining. The case studies were provided to the experts at least a day before the interview.

- A set of open-ended questions to guide the interviews while not restricting the scope of the participants' answers (Paré, 2004).

The interviews were conducted in English using a virtual video conferencing tool and lasted between 60 and 90 minutes. All interviews were recorded, transcribed, and coded afterward (Paré, 2004; Strauss and Corbin, 1998). A similar number of interviews is considered fit for qualitative research of this type, as suggested by Clarke and Braun (2013).

At first, we applied *open* coding of the interviews, unbiasedly examining the data. The authors independently coded the interviews for consistency, then convened to reconcile preliminary coding schemes. This process and subsequent discussions enabled us to decrease the number of codes. Then, we proceeded to code each interview in more detail, allowing for new codes to emerge and existing ones to be adjusted. After that, we compared the patterns of the analyses within each interview and across all interviews to ensure the applicability of the findings. A code was retained for the testing if it appeared in at least two interviews. We then used *axial* coding to identify important code categories related to our research question. This step was carried out to facilitate the classification and the interpretation of the codes before embarking into the final step, that is, interpreting the codes to obtain the second version of the maturity model, i.e., β-P3M.

4. Developing the initial version: α-P3M

As far as the scope of P3M is concerned, we focus on PM as an analytic capability for organizations. It targets two critical stakeholder groups: internal domain experts in PM and PM expert consultants. These internal experts handle PM analysis implementation and execution, while the external ones provide specialized consultancy. Additionally, P3M caters to two audiences: top and operational management within the organization, and external entities like auditors and business partners, who could gain from PM implementation.

Table 1. Description of interview participants

ID	*Industry*	*Location*	*Role and Experience (years)*
A (pilot)	Food & beverage	Australia	Process mining senior engineer (1-3)
B	Finance	South Korea	Senior data engineer (1-3)
C	Manufacturing	Netherlands	Business process improvement manager (5+)
D	Healthcare	Netherlands	Product Owner/Senior Scientist (5+)
E	Healthcare	Netherlands	Program Manager (5+)
F	IT services	South Korea	Data Analyst (3-5)

To create a list of dimensions and sub-dimensions of α-P3M, we considered a set of BPM maturity models in the literature (De Bruin et al., 2005; Dumas et al., 2018; Fisher, 2004; Froger et al., 2019; Rohloff, 2009; Weber et al., 2008), as well as other maturity models on AI-enabled organizational analytics published more recently (Akkiraju et al., 2020; Chen et al., 2022; Dumas et al., 2023; Korsten et al., 2022; Pringle and Zoller, 2018; Saari et al., 2019; Schreckenberg and Moroff, 2021; Vaish et al., 2021). The selection of the maturity model was predicated upon its accessibility and the presence of technologically oriented components within its dimensions and sub-dimensions, as evidenced by the incorporation of the process mining.

When analysing these maturity models, it appeared evident that they often used different terminology to describe similar concepts. For this reason, we compiled a list of the vocabulary used to describe the dimensions and sub-dimensions of the reference maturity models in the literature. When compiling such a list, seven concept categories emerged, as shown in Tab. 2. We also organized the sub-dimensions with similar characteristics from the vocabulary list into groups (not shown in the table for brevity). These groups of sub-dimensions were used to identify the sub-dimensions that could be considered relevant when characterizing PM as an analytic capability.

The seven categories of Tab. 2 resulted in the definition of seven dimensions in α-P3M (Category 1 > Pipeline, Category 2 > Technology, Category 3 > Data, Category 4 > Strategic Alignment, Category 5 > Governance, Category 6 > Culture and Category 7 > People). Hence, α-P3M consists of four dimensions capturing management aspects of PM and three dimensions capturing the information technology aspects of PM. The four dimensions for management aspects (Strategic Alignment, Governance, Culture,

[1]Detailed interview materials and the full specification of α-P3M and β-P3M are available at https://sites.google.com/view/mmpm-research/

Table 2. Categorizing the Dimensions of Existing Maturity Models

Methods (De Bruin et al., 2005), *Process* (Fisher, 2004), *Process* (Weber et al., 2008), *Methods* (Dumas et al., 2018), *Methods and Tools Management* (Rohloff, 2009), *BPM Cycle* (Froger et al., 2019), *Process Design and Collaboration* (Korsten et al., 2022), *AI Operating Method* (Vaish et al., 2021), *Process* (Schreckenberg and Moroff, 2021), *Operation* (Pringle and Zoller, 2018), *Process* (Saari et al., 2019), *Testing and benchmarking, Model Deployment, AI Operational Management* (Akkiraju et al., 2020)	Category 1 > Pipeline
IT/IS (De Bruin et al., 2005), *Technology* (Fisher, 2004), *Asset Management* (Weber et al., 2008), *Information Technology* (Dumas et al., 2018), *IT Architecture* (Rohloff, 2009), *IT/Data* (Froger et al., 2019), *Technology Sophistication* (Vaish et al., 2021), *Technology* (Schreckenberg and Moroff, 2021), *Technology* (Pringle and Zoller, 2018), *Technology* (Saari et al., 2019), *Smart cloud storage* (Chen et al., 2022), *Model goal and offering management* (Akkiraju et al., 2020)	Category 2 > Technology
Data Management (Rohloff, 2009), *IT/Data* (Froger et al., 2019), *Data and Governance* (Korsten et al., 2022), *Data* (Vaish et al., 2021), *Data* (Schreckenberg and Moroff, 2021), *Data* (Pringle and Zoller, 2018), *Data* (Saari et al., 2019), *Smart data acquisition, Big data quality, Smart data analysis, Smart Decision Making, Big Data Security* (Chen et al., 2022), *Data pipeline, Feature Preparation, Model Training* (Akkiraju et al., 2020)	Category 3 > Data
Strategic Alignment (De Bruin et al., 2005), *Strategy* (Fisher, 2004), *Innovative Improvement* (Weber et al., 2008), *Strategic Alignment* (Dumas et al., 2018), *Portfolio and Targeting System* (Rohloff, 2009), *Business/Job, Strategy, Performance and Value*(Korsten et al., 2022), *Impact in Your Business* (Vaish et al., 2021), *Strategy* (Schreckenberg and Moroff, 2021), *Strategy* (Pringle and Zoller, 2018), *Strategy and Management* (Saari et al., 2019), *Content management strategy* (Akkiraju et al., 2020)	Category 4 > Strategic Alignment
Governance (De Bruin et al., 2005), *Controls* (Fisher, 2004), *Standard* (Weber et al., 2008), *Governance* (Dumas et al., 2018), *Process Performance, Process Optimizations* (Rohloff, 2009), *Data and Governance* (Korsten et al., 2022), *Trustworthiness* (Vaish et al., 2021), *Organization and Staff* (Schreckenberg and Moroff, 2021), *Organization* (Pringle and Zoller, 2018) , *Big data management* (Chen et al., 2022)	Category 5 > Governance
Culture (De Bruin et al., 2005), *Culture* (Dumas et al., 2018), *Process Documentation* (Rohloff, 2009), *Culture/Behaviour* (Froger et al., 2019), *People and Culture* (Korsten et al., 2022), *value to end client, Ease of Use* (Vaish et al., 2021), *Product and Services* (Saari et al., 2019)	Category 6 > Culture
People (De Bruin et al., 2005), *People* (Fisher, 2004), *Leadership* (Weber et al., 2008), *People* (Dumas et al., 2018), *Qualification, Communication* (Rohloff, 2009), *People and Culture* (Korsten et al., 2022), *Organization and Staff* (Schreckenberg and Moroff, 2021), *Competence and Cooperation* (Saari et al., 2019)	Category 7 > People

People) are fairly common in maturity models of the BPM capability and, more generally, maturity models of data analytics capabilities. The sub-dimensions that we defined for these 4 dimensions are also relatively common among this type of maturity models.

Conversely, the three dimensions related to information technology (Technology, Pipeline, Data) have been defined based more specifically on the structure of more recent maturity models of (AI-enabled) data analytics. The dimension Technology relates to the actual analytic functionality implemented by an organization; the dimension Data characterizes aspects such as the availability, quality and security of the input data for the analysis, i.e., event logs in the case of PM; the dimension Pipeline concerns the integration of the analytic functionality upstream, i.e., with the landscape generating the input data, and downstream, i.e., where the insights obtained from the analytic functionality should be enacted. The sub-dimensions of the four dimension described above were identified through a similar process of concept grouping using as input the sub-dimensions of the BPM and (AI-enabled) analytics identified by the literature review.

The final stage for this phase involves defining the focus area and identifying the necessary items for sub-dimensions, using the obtained dimensions and referring to the sub-dimensions presented in the literature review. For all dimensions, except Technology, we rely on the traditional five levels of the capability maturity model: initial, managed, defined, quantitatively managed, and optimized. These levels are adopted by most of the maturity models that we considered in our literature review.

The exception is represented by the Technology dimension. For this dimension, based on the recent PM literature stressing the potential of AI in PM implementation (Dumas et al., 2023) and data analytics (Delen and Ram, 2018; Lepenioti et al., 2020), we consider 4 levels:

Descriptive. This level is used when PM functionality is used only "exploratively", i.e., to make sense of the execution of organizational business processes. Process discovery is often the only PM use case in this level.

Diagnostic. This level is used when PM functionality is exploited to extract specific insights regarding the execution and improvement of business processes. In this case, the whole spectrum of PM functionality (e.g., discovery, conformance checking, bottleneck analysis, etc.) can be used, depending on the questions driving the process mining projects.

Predictive. At this level, PM is infused with tools to provide predictive functionality, e.g., to predict process outcomes or time-related measures. This functionality mainly *supports* the decision-makers in the analysis and improvement of existing business processes.

Prescriptive. At this level, the insights from PM, derived, e.g., from predictive analytics or causal analysis, are exploited (semi-) automatically to steer the process execution in certain directions that are considered more likely to achieve specific targets. This is the new frontier of PM (Dumas et al., 2023), aiming at transforming PM from a backward-looking technology analyzing the past executions of business processes to a forward-looking one that enables optimal real-time control of the process execution (based on what learned from the past).

While AI is likely to play a major role in shaping particularly the predictive and prescriptive maturity levels, it has to be noticed that the level definitions in α-P3M are technology-agnostic. The predictive and prescriptive levels, for instance, can be achieved using simple rule-based system to classify the process execution traces, whereas diagnostic techniques, e.g., for bottleneck analysis, may rely on complex deep learning techniques for timestamp prediction.

5. Incorporating the interview feedback: β-P3M

In this section, we first briefly discuss the thematic analysis on the interview transcripts and then we discuss how we obtained the new version of the maturity model (β-P3M) incorporating the feedback from interviews, as elicited using the thematic analysis.

The output of the thematic analysis is constituted by *axial* and *open* codes. We use the axial codes for classifying the type of feedback received during the interviews. The open codes capture specific feedback that we either use to improve α-P3M or consider in future research when deploying the maturity model in real-life case studies.

We have identified four axial codes, thus classifying the expert feedback into four categories. The first category (maturity model feedback) concerns the feedback that we can use directly to improve α-P3M. The other three categories (evaluation, limitations, other suggestions) capture more general feedback for the future steps of this research.

As examples of open codes, Tab. 3 shows two codes from two different categories identified by the axial codes. The first one captures the fact that experts suggest to include data explainability as a sub-dimension in P3M. The second one concerns a positive feedback on the direction of the research expressed by the experts. Generally, the experts have agreed that a maturity model like P3M is needed in industry and could help organizations to better streamline and motivate their process mining initiatives.

The improved version β-P3M (see Table 4 for a summary) is obtained by processing the feedback belonging to the first axial code, i.e., maturity model feedback. We have identified three types of maturity model feedback in the interviews: (i) clarity and understandability of the general wording and definitions in the model, (ii) adjusting and possibly re-defining the existing levels in the model, and (iii) modifications and extensions of the dimensions and sub-dimensions of the model.

General wording. This type of feedback concerned mainly issues with several acronyms used in the level definitions, such as SOP (Standard Operational Procedure) and PDCA (Plan-Do-Check-Action), which were not spelt out in the interview materials. One concern raised by several experts was the definition of the levels in the Consistency sub-dimension of Culture. This dimension focuses on the extent to which the organizational culture is seen as being consistent regarding PM practices. At least two experts asked the interviewer to clarify the meaning of this dimension and both agreed that, after the provided explanation, the meaning of the sub-dimension was clear. Hence, we decided to improve the wording of this sub-dimension in β-P3M, without changing its meaning.

Level Re-definition. Several comments from the experts concerned the clarity and meaningfulness of the definitions of the levels in α-P3M. For each code, we provide an explanation of its interpretation, including a sample quote from the experts, and how we used it to improve in the design of β-P3M.

Code. Tooling in the Pipeline dimension.

Meaning. The α-P3M included a distinction between using ad-hoc (e.g., ad-hoc scripts for process mining in PM4Py or BupaR) or commercial tools (e.g., Celonis, Apromore, Disco) for process mining analyses. The experts convened that such distinction is not important when assessing the maturity of PM. What really matters is the PM functionality that a company is able to use (*"not all companies can use commercial tools right away because commercial tools may not be compatible with their internal systems"* Expert B).

Action taken. Remove any reference to ad-hoc and commercial tools in the definition of maturity levels. Focus the level definitions on PM functionality only.

Code. Management involvement in the Culture dimension

Meaning. This sub-dimension in α-P3M referred only to the top-management support, as it is considered as the crucial part of supportive culture for individual process orientation (Benraad et al., 2022). The experts,

Table 3. Open Coding Examples

Open Code	*Illustrative Data*
Data explainability as sub-dimension	*"from my experience, some cases do not have enough explanation for the data itself For example, we have a lot of variables like age, height, or something like that, and the person responsible for the data is not given an explanation about that variable"* Expert B)
P3M gives concrete advice to company management	*"[This model] can be beneficial to give concrete advice on the direction, how to move to a higher level."* Expert C)

however, highlighted that operational management plays a crucial role in the implementation and execution of PM initiatives (*"[the model says] in the optimized way is executive level sponsorship and in the initial level you have individuals [...] you could also have only executive level sponsorship and no sponsorship by the operational people"* Expert C; *"Executive are saying that I really like to sponsor your project, they are very interested in the functionality but in the end, they are not very happy with the result [That's because] you have problems at the operational level [...] So maybe, for management involvement, you should consider one level below in the organization"* Expert E).

Action taken. Rephrase the levels of the culture sub-dimension to consider also the operational management support.

Code. Business contribution in the Strategic Alignment dimension.

Meaning. The experts emphasized that the definitions of business contribution in the Strategic Alignment dimension could have been confused with the ones of Budgeting. Reduced budgets for business process operation resulting from improvements achieved through PM insights can be seen as a business contribution of process mining. In the maturity model, however, the budgeting signifies a totally different concern, embodied for instance by the need to set transparent and precise budgets regarding PM initiatives (*"it seems that business contribution is more in the broader sense than the budgeting. [...] you should be aware that budgeting can also be a business contribution. To make the business contribution clearer, I think that's good if you could give some examples. And then you should still think that budgeting is still in a separate dimension"* Expert D).

Action taken. We clearly separated business contributions and budgeting in the definition of the levels.

Code. Responsibility in the People dimension.

Meaning. Experts lamented that considering the issue of responsibility within the dimension People could be misleading. The People dimensions normally evaluates the values and attitudes of the human resources involved in the implementation of a capability. Responsibility should not be classified as such. It flows from the establishment of clear organizational policies and roles and, thus, should be a concern of the Governance dimension. (*"For the people [...] responsibility, I would rename it. [in the second case study] you were talking about ownership within the organization, a PM team that is not part of the company"* Expert C).

Action taken. The issue of the responsibility of the PM initiatives was renamed Ownership and moved to the definition of the levels of the Governance dimension.

Code. Include Deployment in the Pipeline dimension.

Meaning. The experts highlighted that it was not clear which part of the maturity model focused on the deployment of PM analyses. That is, similarly to the deployment of AI models in production, they wanted to see a focus in the maturity model on the extent to which the PM functionality was integrated into the systems providing operational support to business process execution (*"With AI, as researchers, we make an output and measure the performance; that's it. But in the industry, we build a model, we measure the performance, and additionally, we implement that in the actual services [...] There, a lot of issues occur. [In PM] I guess many companies may not be ready to implement PM in their services. The level of deployment should also be considered in the maturity model. From the perspective of the company, it's the most important thing"* Expert B)

Action taken. Conceptually, the deployment of PM techniques is already included in the sub-dimension Integration with Operational Application of the Pipeline dimension. This sub-dimension focuses explicitly on the level of integration between PM functionality and operational support in business process execution. In β-P3M, the levels of this sub-dimensions have been updated to include explicit references to the deployment of PM insights.

Dimension extensions. The experts highlighted the need to update the definition of sub-dimensions of α-P3M and to include new sub-dimensions, as detailed next.

Code. Analytic Process sub-dimension in the Technology dimension.

Table 4. Summary of β-P3M

Focus Area	*Capability*	*Level*	*Sub-dimension*
Technology	Assess the information capability in process mining	4 levels	Information Capability
Pipeline	Assess the state of the PM workflow automation (from data gathering to their analysis and diffusion of the results), and how the data are gathered to be integrated and transformed into event logs that can be used for the workflow.	5 levels	Tooling, Integration with Data Source, Integration with Operational Application
Data	Assess the state and availability of data for PM as an analytic capability as well as the associated data security, privacy, and data quality policies and standards.	5 levels	Data Availability, Data Security, Data Quality, Data Explainability, Data Privacy
People	Assess how the human resources are managed in the organization to support PM as an analytic capability.	5 levels	Skill, Responsibility
Culture	Assess the collective values shaping the attitude and behavior when human resources use PM as analytical capability in their job.	5 levels	Use Case Availability, Management Involvement, Adaptability, Consistency
Governance	Assess how an organization sets the formal rules and structures, including their documentation, regarding PM as an analytical capability.	5 levels	Communication, Quality Metric, Documentation System and Compliance Check, Ownership
Strategic Alignment	Assess the strategy that examines the plan of action and roadmap support of PM as an analytic capability.	5 levels	Strategy, Budgeting, Business Contribution

Meaning. The α-P3M includes two sub-dimensions for the Technology dimension: analytic process and information capability. The former was supposed to refer specifically to the analytic capability of PM, i.e., what kind of PM functionality is implemented by a company and what it allows to achieve, while the latter was supposed to refer to the way in which the output of PM is provided to the users, e.g., visualization, dashboards, etc. The experts lamented that this distinction was unclear (*"What do you mean by the analytic process? If I am thinking about technology, I was thinking that you have the tools to find the data. For me, that was something I would expect from the tools"* Expert C).

Action taken. We removed the Analytic Process sub-dimension from α-P3M and integrated its content into defining the levels in the Information Capability sub-dimension.

Code. Data Explainability in the Data Dimension

Meaning. The experts highlighted the necessity for process mining (PM) users to comprehend the data available to them. Frequently, event data for PM, collected by departments like IT, are provided to PM users. Without understanding this data, users may struggle to derive meaningful insights in the first place (*"from my experience, some cases do not have enough explanation for the data itself. We may have a really good quality of data and no missing values, but we don't know what that variable means [...] that happens quite a lot in a real company"* Expert B).

Action taken. We added a new sub-dimension about Data Explainability to the Data dimension. The levels in this dimension track the extent to which an explanation of the data in input to PM is available to PM users.

Code. Ownership in the Governance dimension.

Meaning. As mentioned already above, the experts emphasized that a crucial concern regarding the governance of PM initiatives is the issue of ownership. Clearly establishing the owner(s) of PM initiatives improves the accountability of PM projects and helps to give clarity to PM users (*"I am thinking of ownership [...] you say standardized governance practice, it is not concrete and clear what you want to have [...] do I have owners [of PM and event data] in place? That will make a difference"* Expert C).

Action taken. We added a new sub-dimension about Ownership to the Governance dimension. This sub-dimension captures the ownership of all the aspects of PM initiatives, including the data used as input for PM analyses.

Code. Data Privacy in the Data dimension.

Meaning. An aspect missing in α-P3M is the privacy of the data used in PM. This issue was highlighted as crucial by at least three experts. They suggested that the security and privacy of the data used in PM are fundamental in modern organizations. These concern both the management of private and sensitive information in event logs, as well as protecting the privacy of resources when interpreting and communicating the results of PM analyses (*"In the data dimension, you already mentioned about data security, I think it is better to make [data privacy] separate. Through the data, we can know the hierarchy of this company and how this company works. This is not only about the data security, but the privacy of the people"* Expert F).

Action taken. In the model, we specified that the Data Security sub-dimension solely pertains to storing event data for Process Mining (PM) and derived insights. Concurrently, we established a Data Privacy sub-dimension to address privacy concerns surrounding PM event data and insights.

Evaluation, limitation, and suggestions for the model implementation. Examples of feedback in this category are: regarding the technology aspect, many companies may be satisfied with the descriptive Technology level and may not want to move to the predictive/prescriptive level; or that we should consider that P3M may not be applied to a company as a whole, but only within specific business units that are applying PM.

6. Conclusions

This paper has presented the design and testing with industry experts of P3M, a maturity model for process mining as an analytical capability. Following an iterative approach, a first version obtained by integrating the literature on maturity models for BPM and (AI-enabled) data analytic, has been improved using the feedback from in-depth qualitative interviews with five PM industry experts. P3M extends the current literature on the process mining organizational perspective, by providing, instead of a static view on PM success factors (Mamudu et al., 2023), organizational guidance for improving the PM analytic capability over time.

The development of P3M thus far has several limitations and opportunities for future work. While P3M has been tested with practitioners for its development, the deployment of P3M in a real-world organization is still missing and subject of ongoing work. The testing of P3M relied mainly on participants selected from the authors' own network, which may limit the internal validity of our research method. In the future, we will strive to involve multiple participants per organization to capture diverse perspectives and a larger sample size to analyze control variables such as work and process mining experience, organization size, and sector to confirm the robustness of P3M.

Additionally, future research should evaluate P3M more quantitatively against other quality criteria, such as usefulness, utility, quality, or efficacy, using objective performance measures such as business contribution to help organizations prioritize their efforts in improving their maturity for different capabilities.

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