AI Implementation Maturity in Process Mining*

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Abstract

Integrating Artificial Intelligence (AI) technology in Process Mining is perceived as an inevitable catalyst that will improve the quality of the process analyses in Business Process Management (BPM). However, the uptake of AI in BPM and process mining in real-world organizations are still minimal. In this context, maturity models are often seen as a way for organizations to quantify their achievements in implementing new technology. This research will develop a maturity model to measure AI implementation in process mining initiatives and the methods to guide organizations in growing their capabilities. In particular, the model will explore the critical points in implementing AI in the process mining cycle and how AI may become a critical success factor that will provide business benefits. This paper briefly describes the methodology we will adopt and the preliminary results of this research.

Keywords

AI implementation, maturity model, process mining, business process management

1. Introduction

Process mining is vital in enabling data-driven analysis in BPM. BPM allows process owners to visualize business flows and analyze business process performance. Process flows can be used to analyze operations according to business strategy, improve processes, assess business process performance, and identify obstacles that interfere with business efficiency.

With the rapid advancement of AI in various fields, there is also a significant opportunity for AI infusion in process mining to reduce costs or provide a better user experience[1]. One of the most extensive support that AI can give in process mining is the predictive analysis capability [2, 3]. This allows decision-makers to anticipate what could happen in the future execution of a process based on historical data captured in event logs. From the top management or managerial decision-making standpoint, these capabilities are supposed to benefit the business perspective more. At the operational level, it makes it possible for more resource allocation or optimization.

At the same time, integrating AI in process mining can provide a leap in the quality of information needed for decision-making by process owners. As with other ways of improving business processes, integrating AI tools in Process Mining also comes with risks. In their analysis of risks in BPM, Zur Muehlen & Ho [4] generally identify the following risks for a BPM

Proceedings of the Demonstration&Resources Track, Best BPM Dissertation Award, and Doctoral Consortium at BPM 2022 co-located with the 20th International Conference on Business Process Management, BPM 2022, Munster, Germany, September 11-16, 2022

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planner: a) a mismatch of techniques used in the different phases of the process life cycle, b) a lack of clarity on who is responsible for the individual steps or their results and c) a mismatch of process design, automation, and evaluation objectives (i.e., goal mismatch).

When applying AI in process mining, various challenges will be faced from a management standpoint, including the readiness of the organization to start or accept the new challenge of applying AI. Assessing this readiness requires methods and tools to evaluate an organization's capability and guide the change management plan to improve AI adoption in process mining. In short, the notion of a "maturity model" fit the organization needs in this context. A maturity model will represent the progressions in a particular focus area and the required steps to increase an organization's capabilities in such a focus area.

In this Ph.D. project, we focus on developing maturity models and the related tooling for AI adoption in process mining. First, we aim to use the literature review to understand the current maturity model in BPM, AI, and process mining. This literature review will also help to identify the artifact's (i.e., the AI in process mining maturity model) requirements. Then, the design and development stage will have several iterations. Each iteration will involve demonstration, interviews, and discussion with experts and practitioners. After having developed the maturity model, we will also develop and validate additional tools for using the model in the real world. The models and tools developed in this Ph.D. project will also be communicated to the parties expected to benefit from using them.

The following section discusses an overview of the research methodology adopted in this project and its implementation. The last section discusses the results achieved thus far in the project and opens issues for the future.

2. Research Methodology and Implementation

The proposed research approach, depicted in Figure 1, is based on the steps from the design science research methodology for developing maturity models and the related methods [5, 6, 7, 8]. Design science research is a methodology developed in the field of information systems (IS), to solve practical problems by designing and developing artifacts [7, 8].

We envision this Ph.D. project will have six phases, from a problem definition to the communication process of research results. The research results are expected to contribute knowledge that can be used by companies and process mining technology providers to measure the success rate of AI implementation in process mining and provide motivation and instructions for further improvement. The following section will describe every step to get the final model.

2.1. Problem Definition

A rigorous and structured method is particularly beneficial for the literature review stage in information systems research [9]. In this step, we will define the research motivation through problem awareness, survey the literature to identify the state of the art of the various maturity models and compare it. The stages of the literature review will follow the guidelines of Kitchenham& Charters [10, 11] to structure the review. Potential keywords for searching in scientific databases are the combinations of the terms "AI maturity","AI in process mining","IS maturity model", and "business process management".

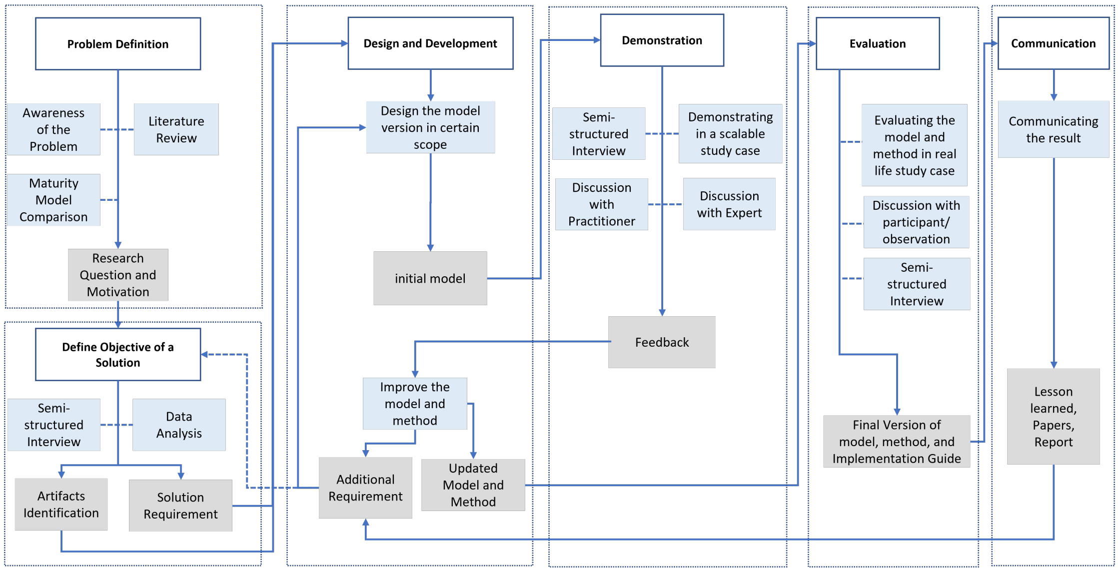

Figure 1: Research Framework

Based on the results, we will analyze the existing approach, find the scope, see the problem that emerged from previous development, and future suggestions for the research goal. This stage will construct relevant information needed for the next scene.

2.2. Define the Objective of a Solution

The basic knowledge from the previous stage will help define the solution and its requirement. We will conduct semi-structured interviews and data analysis to enrich the "construct" definition from the practitioner's side. Some artifacts identified in this stage include the maturity model and method for assessment and improvement.

2.3. Design and Development

The steps in this stage are taken to get the model will adopt design science research, which performs several iterations to get the appropriate model. Each iteration will define focus area, domain, capability, levels, assessment questions and instruments, dependency, also improvement actions [12]. Iterations can be carried out on a smaller scope to minimize the existence of essential points that are not measurable if they are directly applied to process mining. One design choice in this direction is to consider a first iteration focused on predictive process monitoring [2, 13] as a field of process monitoring where AI is more often adopted. This stage will carry the initial model result to get feedback from the demonstration and evaluation stages and refine the artifacts.

2.4. Demonstration

The next step after getting the initial model of the artifacts is to get the feedback from the demonstration in different study case scopes and semi-structured interviews with practitioners and/or academic experts. This feedback may give additional requirements for the artifact, complete the model and method, and fulfill the cycle of design science research. At this stage, it is also necessary to determine the right strategy to introduce the artifacts to the respondents.

2.5. Evaluation

The evaluation stage carried out on the maturity model is expected to benefit the problem definition. Models and methods must be evaluated in real-life observations. The observations will show the extent to which the model is genuinely applicable and relevant to the needs of its users. The repair iteration process can be repeated for the user guide if the adjustment needs are found.

2.6. Communication

Automation acceleration in process mining will leverage the BPM cycle to the next level. It will make a business-critical application for the most efficient and transparent processes by showing the model, tools, and guidance. Lessons learned from the previous stages for AI implementation in process mining will define the continuity in design science research, whether the cycle will be repeated or released in reports or publications. The final model will contribute to the business process management implementation by paying attention to digitizing the latest technology with AI.

3. Conclusions: Achieved Results and Open Issues

The preliminary literature review used related keywords regarding maturity models in AI, process mining, IS capability, and BPM. The results from the literature review are used to compare the existing maturity models. The comparison and analysis become input for the second stage, which defines solution objectives.

Although many BPM maturity models (BPM MM) have been developed [14, 15, 16, 17, 18, 19] to measure the readiness or capability of organizations to achieve success in BPM initiatives, these models generally touch on the dimensions at the organizational level. The Object Management Group (OMG) has also released highly detailed maturity levels for BPM, with levels of detail that is challenging for organizations to implement efficiently [17].

The models have several grouping: fixed-level or staged, focus area-based approaches, or one-size-fits-all. One of the popular oncomings from the current BPM MM is the capability maturity model (CMM), developed by the Software Engineering Institute at Carnegie Melon University [20]. It defines five maturities levels: initial, repeatable, defined, managed, and optimizing. Focus area-based approach was explained by van Steenburgen et al., and Bekkers et al. described the situational assessment method as one-size-fits-all [21, 12]. Van Looy et al. [22] estimate that more than 150 business process maturity models address one or more BPM areas.

Some technology providers [23, 24, 25] also released maturity levels for BPM and informative articles to classify each level's achievements. However, several literature review papers mention that the assessment process for the maturity model was not well defined [26, 27, 28].

Machine learning and deep learning drive all the spotlight on the massive implementation of AI in various fields. Maturity models have been developed to measure AI implementation in companies. The A-AIMM [29] is an Artificial Intelligence Maturity Model for the Auditing Process, PriMa-X [30] assesses prescriptive maintenance by machine learning. Schreckenberg & Moroff [31] looks at the maturity level of elements using the example of demand forecast. These usually apply to specific case studies [32, 33] or only focus on the latest technology innovation, such as big data, security, data analysis [34], and infrastructure for AI [25]. This rapid AI implementation will also accelerate challenges in its adoption in BPM, especially in process mining. Therefore the need for the model and methods that help the organization assess the readiness and give guidance to achieve better capabilities will also leverage.

As far as the maturity model development is concerned, the first iteration of it will focus on predictive process monitoring [2, 13, 3]. This is the process mining task where most implementations of AI (mainly machine learning) can be found. The initiate model uses a focus area-based approach to make it more flexible when assessing or determining improvement actions. We have identified a set of dimensions for the maturity of predictive process monitoring initiatives. Specifically, we have defined separate dimensions for the management and technology domains, respectively. The next stage requires an expert review to ensure that these dimensions and the associated levels are appropriate and understandable by the practitioners and academic experts. We will employ discussion and semi-structured interviews when approaching the experts.

In this initial phase of the research, we have realized that there are several challenges regarding the definition and evaluation of maturity models for AI in process mining, such as:

- Both BPM and AI maturity models in the literature describe the maturity levels but do not provide prescriptive guidance regarding how organizations can improve their current levels. This can be part of more general guidelines for the people in charge of administering the maturity level assessment and improvement.
- Implementing predictive process monitoring, let alone more complex AI tools, in process mining by organizations will deal with data disclosures. This will pose some challenges for the model and methods demonstration and evaluation. For instance, defining and interpreting a balanced capability level in real-world organizations' study cases may be challenging.
- Higher maturity of AI adoption in process mining is supposed to improve an organization's decision-making capabilities in the BPM life cycle. The need for maturity models in this area will surge as an essential business requirement for real-world companies. In that case, various cultures and stages of an organization's current business model can be challenging in determining its artifacts content and acceptance indicators at each decision step in design research science.

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