Bus Inf Syst Eng 63(5):483–490 (2021)
https://doi.org/10.1007/s12599-021-00718-8

EDITORIAL

A Five-Level Framework for Research on Process Mining

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Published online: 7 September 2021

1 Introduction

Process Mining is a novel technology that helps enterprises to better understand their business processes. Over the last 20 years, intensive research has been conducted into various process mining techniques. These techniques support the automatic discovery of business process models from event log data, the checking of conformance between specified and observed behavior, the identification of various variants of a business process, non-compliant behavior, performance-relevant insights, and so forth.

Research on process mining has mostly focused on devising new or better algorithms (see van der Aalst 2016; Augusto et al. 2019a). There are a few exceptions, among others the following. van der Aalst et al. (2007) were the first to discuss process mining from the perspective of applications in industrial practice. Jans et al. (2014) applied process mining techniques to enrich audit evidence during a financial statement audit. vom Brocke and Mendling (2018) and vom Brocke et al. (2021) present various applications of process mining in hospitals, insurances, software usability analysis, and logistics.

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In recent years, process mining has seen an increasing uptake in enterprises (Dumas et al. 2018), and has thus become an integral part of their daily business process management. Companies like Celonis, Fluxicon, Signavio, and Software AG are among the roughly 20 companies that Gartner monitors. As Kerremans (2019) from Gartner states, enterprises adopt process mining tools in order to support business process improvement, auditing and compliance, process automation, digital transformation, and IT operations (in order of decreasing importance).

Some contributions have been made towards understanding how process mining has an impact in an enterprise setting. Much of this research focuses on methodology and application domains. For instance, van Eck et al. (2015) and Aguirre et al. (2017) describe methodologies how process mining projects can be conducted, and Maruster and van Beest (2009) provide a methodology how business processes can be redesigned with the help of process mining. Mans et al. (2013) discuss success factors for such process mining projects. Examples of domain-specific proposals in healthcare are Rebuge and Ferreira (2012) and Fernández-Llatas et al. (2015). Thiede et al. (2018) find applications for digital as well as for physical processes, which are investigated using data from single systems, across systems, and across boundaries. Process mining has even been identified as a strategy of inquiry for studying organizational change (Grisold et al. 2020).

What is largely missing so far is research on how enterprises adopt process mining technology, how they integrate it into their information systems landscape, and which kind of effects emerge from this adoption. Effects are complex and unfold at different levels of the organization (Grisold et al. 2021). They are connected with organizational culture and the governance structures, to name but a few. Leonardi and Treem (2020) have coined the term behavioral visibility, a term that nicely emphasizes what process mining affords. The "datafication" of private and professional lives creates digital traces in various systems which can be analyzed by means of process mining techniques. In this way, process miming has the potential to afford behavioral visibility of various actions not only inside but also outside an organization. Obviously, many challenges arise from such large-scale behavioral visibility, including ethical ones. Therefore, more interdisciplinary research on the application of process mining from an enterprise perspective is needed.

In this editorial, we develop a framework for systematically discussing many of the associated concerns that emerge from adopting process mining in an enterprise setting. Our framework can be used to analyze the effects of process mining at different levels of investigation. In the following, we first provide a brief overview of process mining and its essential concepts. Then, we introduce our framework and discuss potential relevant research perspectives for each of its five levels.

2 Techniques, Tasks and Parties Involved in Process Mining

Enterprise information systems automatically log data during daily process executions. Process mining is a family of techniques that extract process knowledge from this logged process data. These techniques integrate concepts and ideas from machine learning and data mining on the one hand and process modeling and process analysis on the other hand (van der Aalst 2016).

In essence, process mining techniques support process discovery, conformance checking, process variant analysis, and process performance analysis (Dumas et al. 2018). *Process discovery* is the act of discovering a process model from event log data. This process model represents the real, observed behavior. *Conformance checking* focuses on the relation between a process model and the observed behavior (Carmona et al. 2018). Conformance checking techniques identify and measure the discrepancies between model and log. Researchers mainly use conformance checking to assure the quality of the discovered process model, i.e., to which extent this model accurately represents the logged behavior. In this context, the event log is taken as reference against which conformance is checked. Practitioners are more often interested in identifying which cases violate the behavior prescribed by the model. This means that the process model is taken as the norm to check conformance against. *Process variant analysis* addresses the question which variants of the process exist and which characteristics they are correlated with. Corresponding techniques build for instance on clustering and the analysis of factors. *Process performance analysis* is concerned with the analysis of time, costs, quality and flexibility of a business process based on event log data. In this way, measures can be identified to speed up the process, save costs, improve quality, and extend flexibility.

Technical research on process mining has primarily focused on process discovery and conformance checking. Different algorithms have been proposed for both tasks at hand. For process discovery, the Inductive Miner (Leemans et al. 2014), the Evolutionary Tree Miner (Buijs et al. 2014), the Split Miner (Augusto et al. 2019b) and the ILP miner (van Zelst et al. 2018) are examples of recent techniques. For conformance checking, techniques can be divided into three types of approaches. Some techniques rely on checking whether the observed behavior is *compliant with a set of rules* (e.g., Maggi et al. 2011). These rules function as a norm to check against, similar to controlling functions in organizations. Other techniques are based on the *replay* of the logged behavior on the process model (e.g., Rozinat and van der Aalst 2008). Finally, techniques based on *alignments* build on aligning the process executions with the closest path in the process model, which provides basis for calculating a notion of distance (e.g., De Leoni and van der Aalst 2013).

When organizations apply process mining, they do it by using a software tool from one of the numerous vendors. A *process mining tool* offers a set of analysis techniques for process analysts in a user-friendly way. The selection of the tool should reflect the requirements of the users. Often, these process mining users are *process analysts* who have the required skill set. Not only are they familiar with the field of process mining, but they also have expertise in an application domain. An experienced process analyst is a person who understands the organization's challenges, gets the right people on board, and is then capable of translating the business needs into specific analysis questions. Regarding process mining, process analysts have to develop an understanding which questions could be answered based on process event data. To this end, they interact with process participants, process stakeholders, and external partners. *Process participants* are those who work on individual tasks that collectively define overarching business processes. Their coordination and collaboration is logged by enterprise information systems, establishing the basis for applying process mining. *Process stakeholders* essentially include managers who have an interest in business processes operating well. They set the agenda for analyzing and improving business processes. Finally, *system engineers* provide expertise in which data enterprise information systems store and how event logs can be extracted.

A last, related party in the context of process mining is the group of *external partners*. These are the parties that are not directly involved in the process mining project, but are often considered in process analyses. The two most often analyzed business processes are order-to-cash and procure-to-pay. Both directly relate to external partners, namely customers and suppliers.

The described techniques, their corresponding analysis tasks, and the parties involved in process mining influence its success.

3 A Framework for Research on Process Mining

Process mining unfolds effects at different levels. For our framework we take Hevner et al. (2004) as a starting point, who describe a technical, a people and an organizational level of analysis. We refine this set to five levels, distinguishing an individual and a group level, and adding an ecosystem level (see Fig. 1).

At each level of the research framework, we identify specific phenomena of interest, key candidate theories to apply and further develop, and we pose a set of tangible research questions to be addressed as part of an agenda for future research. Please note that the separation of different levels is conceptual and, therefore, artificial. Even though effects span across these levels, the distinction of different levels can help to provide conceptual clarity.

3.1 Technical Level

Various concerns apply to researching process mining at the technical level. Much of the contributions at this level can be understood as pieces of engineering, and most of this engineering is focused on developing novel algorithms for different process mining tasks. These algorithms support the essential sets of various process mining techniques. Research on process mining at the technical level can be framed as a specific category of algorithm engineering.

Mendling et al. (2021) distinguish both design and knowledge contributions in the context of algorithm engineering:

Design contributions can be either design improvements or design exaptations. *Design improvements* present algorithms that perform better in at least one of the important performance dimensions such as execution time or output accuracy. For instance, the Split Miner (Augusto et al. 2019b) was presented as a design improvement providing high and balanced fitness and precision. *Design exaptations* demonstrate the applicability of established algorithmic designs for newly described tasks. An example is the work by van der Aa et al. (2018), which presents a conformance checking technique that is able to use text descriptions as normative specifications.

Knowledge contributions can be either performance propositions, sensitivity propositions, or explanatory propositions. The survey and comparison of state-of-the-art algorithms by Augusto et al. (2019a) focuses on *performance propositions*. *Sensitivity propositions* can be investigated with internal, design-related variations and external conditions as factors. The research by Di Ciccio et al. (2013), which studies the effect of noise on declarative process discovery, belongs to this category. Finally, *explanatory propositions* bring to the foreground the mechanisms of how design characteristics affect performance. For example, the study by Augusto et al. (2021), which investigates log complexity measures as predictors for the accuracy of process discovery, is in this category.

Fig.1 Process mining research framework

Level	Focus
Ecosystem	The effects of process mining on inter-organizational relations, e.g., value chains and networks.
Organizational	The effect of process mining on operations and value creation in organizations, e.g., organizational success.
Group	The effects of process mining on people's interaction and mode of work, e.g., teams.
Individual	The effects of process mining on people's perception and behavior, e.g., users.
Technical	The design of process mining technology, e.g., algorithm engineering.

Much of the research on process mining at the technical level emphasizes design contributions and provides some knowledge contribution as an evaluation of the design work. Mendling et al. (2021) stress that various *validity concerns* have to be considered for such evaluations of process mining design contributions: algorithm engineering in general is subject to threats that relate to ecological validity, implementation validity, justification validity, logical validity, internal validity, external validity, construct validity, and conclusion validity.

3.2 Individual Level

Different categories of users work with process mining tools and their implemented algorithms and analysis techniques. We have identified users such as process analysts, process participants, process stakeholders, and external partners (Grisold et al. 2021). They use these tools in order to accomplish goals that are associated with process-mining-related tasks. Often, these tasks are not isolated, but embedded in BPM projects (Dumas et al. 2018) and BPM programs (vom Brocke et al. 2021). Some of the methodological specifics of these projects have been highlighted by van Eck et al. (2015), Aguirre et al. (2017), Maruster and van Beest (2009) and Mans et al. (2013), partially inspired by the CRISP-DM procedure (Martínez-Plumed et al. 2019). Ailenei et al. (2011) describe a set of 19 different analysis tasks including discovering the distribution of cases over paths, checking exceptions from the normal path, resources involved in cases, longest waiting times, identification of business rules. All of them can be directly supported by analysis based on process mining.

The task perspective plays a role for understanding why users adopt and use technology such as process mining tools. Seminal work towards the technology acceptance model emphasizes that perceptions about usefulness and ease of use are central for usage (Davis 1989; Davis et al. 1989). On the one hand, this is a question of how clear, understandable and easy to learn a technology is. On the other hand, different dimensions of usefulness such as job performance, work productivity, and overall effectiveness are equally important. Acceptance is indeed an issue for process mining (Grisold et al. 2021). According to the technology acceptance model, users are most likely to adopt process mining tools when they are easy to use and at the same time improve their effectiveness when working on process analysis tasks.

While the technology acceptance model explains when users are inclined to use a software tool, the task-technology fit model puts more emphasis on the actual task performance. Goodhue and Thompson (1995) stress that task characteristics and technology characteristics have to fit one another in order to provide a positive impact on performance. Applied to process mining, the fit model suggests that the analysis capabilities of a process mining tool should meet the demands of the tasks that a process analyst and other users are confronted with in the context of a BPM project. The tasks described by Ailenei et al. (2011) or the BPM use cases by van der Aalst (2013) could serve as basis for assessing such a fit.

Several additional perspectives on technology use have been integrated into the most recent version of the unified theory of acceptance and use of technology by Venkatesh et al. (2003, 2016). In essence, this theory posits that behavioural intentions are influenced by performance and effort expectancies, as well as social influence. These intentions materialize into actual technology usage under consideration of additional facilitating conditions. For process mining, social influence is a particularly interesting construct that can potentially play into different directions: from bottom up, it can produce resistance against creating transparency, eventually hampering adoption and use; from top down, social pressure can be imposed to make use of analysis capabilities of process mining. Such forces represent higher-level contextual factors (Venkatesh et al. 2016) that together with individual-level contextual factors influence acceptance, use, and eventually outcomes.

3.3 Group Level

We have described several groups of actors that are involved with business processes and corresponding BPM projects, namely process participants, process owners, process managers and process experts of multiple local teams. Notably, process participants and process managers are the largest and most diverse of these groups. A single business process can involve several departments and their corresponding managers and process participants who might not even be in the same reporting line. This setting provides various challenges for any initiative to improve such business processes (Markus and Jacobson 2015).

Before any improvements can be achieved, a shared understanding of the business process by all of the involved persons has to be established. In their work on the principles for good BPM, vom Brocke et al (2014) have formulated the principle of a joint understanding, meaning that BPM should not be the language of experts but create shared meaning. The BPM lifecycle addresses this point by stressing the need to discover and analyze the as-is process. Work on knowledge management in information systems research emphasizes this point, too. Nelson and Cooprider (1996) demonstrate that information system related activities require mutual trust and mutual influence, and that shared understanding and appreciation is key for translating mutual trust and influence into good performance. Process mining, in turn, might presumably help to increase both mutual trust and influence thanks to evidence-based insights into the process, as well as shared understanding by providing process representations that span the boundaries and the lines of visibility of the groups involved.

One of the relevant mechanisms for explaining the impact of process mining in this context are boundary objects. Star and Griesemer (1989) discuss cooperation without central control. They observe that boundary objects facilitate this cooperation thanks to three properties: interpretive flexibility, the needs of information and work processes, and dynamics of usage. Process mining tools can be analyzed using this lens, surfacing this facilitating role for the cooperation between, among others, process analysts, participants, and managers. The information needs of these groups differ such as the interpretations of representations generated by process mining tools, but they are not arbitrary. In this way, dynamic usage can converge towards standardized objects or systems (Star 2010), where boundary spanners-in-practice and boundary objects-in-use leverage cooperation (Levina and Vaast 2005).

Another relevant mechanism associated with process mining is behavioural visibility (Leonardi and Treem 2020). The digitalization of the work place has provided the means for tracking and analyzing behavior. An important observation regarding this digitalization is that the effort for obtaining behavior-related information has drastically declined as has the potential to analyze patterns (Leonardi and Treem 2020). Process mining tools leverage this behavioral visibility into work processes in organizations, revealing patterns, causes and motives (Leonardi and Treem 2020) by corresponding analysis functionality. In this way, new affordances and constraints (Norman 1999) are introduced into the way in which BPM projects are conducted. The article by Eggers et al. (2021) in this special issue discusses the mechanisms by which behavioral visibility increases process awareness, and eventually fosters process change.

We envision process mining in an enterprise setting to change the governance models for process management. Given the capacity to generate process knowledge quickly and continuously, based on real-time process data, process work will be less concerned with inquiring about processes and manually crafting processes models. Process mining will lead to more ad hoc investigations into processes and more real-time and data-driven decision making. Instead of working on processes in large teams of process analysts, investigations into processes could be organized in cross-departmental meetings, e.g., held on a weekly basis and taking immediate action. Hence, process mining also stimulates research on the organization of the process work.

3.4 Organization Level

Technical implementation, individual adoption, and actual use of process mining tools are a prerequisite for any impact at the level of organizational performance. The mechanisms at the group level reveal how process mining can unfold its impact at the level of the larger organization. The information systems success model makes exactly this point by highlighting the impact of system quality, information quality, and service quality on individual use and usage satisfaction; these eventually translate into net benefits at the individual and at the organizational level (DeLone and McLean 1992, 2003; Petter et al. 2008).

The theory of effective use drills down into the mechanisms surrounding information quality. In essence, effective use builds on a chain of transparent interaction, representational fidelity and informed action, which all contribute to efficient and effective performance (Burton-Jones and Grange 2013). Trieu et al. (2022) contextualize effective use in a business intelligence context and foreground business intelligence system quality, data integration, and an evidence-based management culture. For process mining, these constructs might serve as potential constraints to the affordances a process mining tool provides.

What is partially hidden behind the service quality construct in the success model is a capability perspective. BPM-related capabilities have often been described as dynamic capabilities, which are directed towards organizational problem solving (Niehaves et al. 2014). The BPM-related capability areas presented by Rosemann and vom Brocke (2015) are specifically relevant in this context. The Delphi study by Martin et al. (2021) in this special issue uses them as a framework for identifying challenges and opportunities arising from process mining. The experts in this study describe more opportunities related to strategic alignment, methods and information technology, while more challenges are identified for governance, people and culture. Also in this special issue, Eggers et al. (2021) emphasize that the benefits that process mining offers are contingent to governance and implementation approaches.

Process mining can also be understood as a specific big data analytics capability. The framework by Grover et al. (2018) offers insights into how such capabilities along with an underlying infrastructure unfold an impact in different value dimensions. They describe that different value creation mechanisms are key to the capability realization process, including organization performance, business process improvement, product and service innovation, and consumer experience as much as market enhancement (Grover et al. 2018). Finally, Grover et al. (2018) point to various other theoretical logics that can be useful for studying big data analytics, namely resources, alignment, real options, dynamics, and absorptive capacity. These might be equally relevant for process mining.

3.5 Digital Ecosystem Level

So far, process mining has largely been restricted to the boundaries of central organizations. Martin et al. (2021) identify opportunities and challenges for process mining, and several of these directly relate to the ecosystem in which a company operates. The opportunities described by experts of their Delphi study relate to how process mining can facilitate value creation by fostering collaboration across organizational boundaries.

At this point, some research has been conducted on how process mining can be implemented at an inter-organizational level. Before organizational and strategic challenges can be addressed, various conceptual challenges have been overcome for constructing an integrated coherent data representation of the process across involved organizations (Gerke et al. 2009; Dumas et al. 2018, Chapter 11). Opportunities arise from the increasing uptake of blockchain technology for business processes (Mendling et al. 2018; Pufahl et al. 2021). Specific technical solutions such as the extraction of blockchain data for processes have been devised (e.g., Klinkmüller et al. 2019; Mühlberger et al. 2019). Hobeck et al. (2021) demonstrate which kind of insights can be derived by help of their case study with Augur.

Grover emphasizes in his interview with Mendling and Jans (2021) in this special issue that "the digital" defines new challenges for researching business processes. In this context, also new challenges arise. For instance, privacy is a concern once data is analyzed that is related to people who are not part of the same organization as the one in which the data is analyzed or where the generated insights are used (see Mannhardt et al. 2019). This is particularly relevant for mining data from the Internet of Things (Michael et al. 2019) and applications in healthcare (Pika et al. 2020).

4 Future Research Directions

In this editorial, we have identified connections between process mining and many established concepts and theories on information systems. We described a five-level framework including a technical, individual, group, organization, and ecosystem level. The impact of process mining can be investigated at each of these levels and across them.

In our call for papers for this special issue, we raised several research questions (vom Brocke et al. 2020a, b):

- How is process mining used and adopted at the enterprise level?
- What is the potential of using various types of data in process mining?
- How does process mining complement other approaches and technologies?
- How do enterprises build suitable data sets?
- What are the implications for management of using process mining?
- Which governance structures do enterprises develop for process mining?
- How do enterprises calculate the business case of process mining?
- How does process mining change organizational culture?
- How does process mining change the required skill sets of tool users?
- How is process mining integrated into the IT landscape?
- How is process mining integrated with existing business process methodologies?
- How is process mining adopted in specific application domains, e.g., accounting, health, finance, HR, tax, etc.?
- How is process mining used to support digital transformation initiatives?
- What strategic implications for enterprises emerge from process mining usage?
- What is the business impact of adopting process mining?
- What is the overall business value of process mining?
- What is the transformative nature of process mining at the enterprise level?

The two research articles (Eggers et al. 2021; Martin et al. 2021) and the interview (Mendling and Jans 2021) published in this special issue answer some of these questions. Many of the questions, however, remain open.

The process mining research framework also shows that contributions from different disciplines are needed to further understand and develop the potential of process mining. On a technical level, for instance, computer science makes important contributions to algorithm engineering. Information systems research, in addition, has a great opportunity to cover the many socio-technical aspects related to process mining use on the individual, group, organizational and ecosystem level.

Specifically, both behavioral and design-oriented contributions are needed (Hevner et al. 2004). Based on a better understanding of process mining use in an enterprise setting, prescriptive knowledge can be gained to support interventions in practice (vom Brocke et al. 2020a, b), e.g., by models and methods for value identification and value realization through process mining. We hope that this special issue will trigger a range of research activities to address many of these research questions.

Funding Open Access funding enabled and organized by Projekt DEAL.

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