

# TURNING BIG DATA INTO VALUE: A LITERATURE REVIEW ON BUSINESS VALUE REALIZATION FROM PROCESS MINING

*Research paper*

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## Abstract

*In recent years, process mining has emerged as the leading Big Data technology for business process analysis. By extracting knowledge from event logs readily available in information systems, process mining provides new ways to discover, monitor, and improve processes while being agnostic to the source system. Despite its undisputed practical relevance, we have a limited understanding of how organizations realize value potentials from applying process mining in different organizational contexts. Addressing this gap, we conduct an assessing literature review by analyzing 58 papers from the literature on process mining to synthesize the existing knowledge on business value realization from process mining. Our analysis is guided by adopting the perspective of process mining embedded within its organizational context. By analyzing the dimensions of the nomological net around process mining, we contribute to the broader research field of Big Data value realization twofold. First, we uncover which benefits organizations gain by applying process mining. Second, we analyze the organizational capabilities and practices that influence how organizations use and implement process mining. In addition, we reveal how process mining leads to business value realization. Based on these results, we suggest directions for future research on process mining in the organizational context.*

*Keywords: Big Data Analytics, Process Mining, IS Value Realization, Antecedents.*

## 1 Introduction

Recent years have marked a paradigm shift in the way organizations leverage data for decision-making (Abbasi et al., 2016). Formerly, organizations used to collect data in discrete time intervals along structured paths for preconceived organizational purposes (Constantiou and Kallinikos, 2015), for instance, by monthly collecting sales data to calculate financial key performance indicators. Nowadays, organizations need to deal with vast amounts of unstructured, heterogeneous data that originate in high velocity from various sources inside and outside the firm (Jones, 2019), including social, sensor-based, or machine data (Abbasi et al., 2016). This paradigm shift is rendering established mindsets and practices for deriving knowledge from information obsolete (Kuhn, 1962), thus, coercing organizations to build new capabilities and practices for analyzing and using Big Data (Constantiou and Kallinikos, 2015). Summarized under the term Big Data Analytics (BDA), firms now strive to integrate, preprocess and analyze data in real-time to “*wring every last drop of value*” from business processes (Davenport, 2006, 2).

As organizations are always on the quest to optimize business processes continually through extracting and interpreting process data for decision-making (Constantiou and Kallinikos, 2015), process mining has received increased attention during the last decade, both from research and practice. Process min-

ing is a BDA technique aimed at discovering, monitoring, and improving real business processes (van der Aalst, 2011). By analyzing large amounts of event data that are readily available in today's information systems, process mining depicts business processes as they are executed in an organization (van der Aalst, 2011, van der Aalst and Weijters, 2004). The German process mining start-up underpins the practical relevance Celonis with a valuation of over \$1 billion (Steger, 2018) and the predicted three- to fourfold increase of the current process mining market of \$160 million within the next years (Kerremans, 2019). In addition, a recent survey of 360 German companies shows that 81% have at least partially analyzed their process landscape with process mining (Reeder et al., 2019). These examples illustrate how process mining – as currently the only BDA technology available for data-driven end-to-end business process analysis (van der Aalst, 2011)—is meeting organizations' increased demand to gain transparency and improve their processes to help them to adapt to quickly changing business requirements and customer expectations (Altinkemer et al., 2011).

Nevertheless, actualizing business value from BDA has proven to be difficult for firms. In a recent study, Capgemini found that only 27% of international organizations consider their BDA initiatives as “profitable” (Capgemini, 2016, 2). Gartner reported that international organizations abandon 60% of BDA initiatives already in the pilot phase (Heudecker and Hare, 2016). In addition, organizations that aim to adopt BDA successfully face multiple challenges. These challenges are not only technological, such as the heterogeneity and varying quality of data (Baesens et al., 2016) or the high speed of data creation (Abbasi et al., 2016), but also encompass a socio-technical dimension. The availability of vast amounts of data per se does not lead to strategic advantage and business value. It is the socio-technical process of deriving insights and acting upon these insights that create business value (Grover et al., 2018, Constantiou and Kallinikos, 2015). Still, research lacks knowledge on the underlying antecedents and processes that allow organizations to implement and use BDA IT artifacts for deriving and leveraging valuable insights (Abbasi et al., 2016). Following Benbasat and Zmud (2003), we consider it to be at the heart of the IS discipline – with its unique predisposition to study technology concerning its individual and organizational use – to investigate the BDA IT artifact within its rich socio-technical context. Thus, we are following the call of Grover et al. (2018, 392) for IS research to understand “*the mediating process and mechanisms*” that enable organizations to realize business value from BDA. Focusing on the case of process mining as a contemporary BDA technology of great practical importance, we consequently aim to answer two research questions: (1) *Which value potentials do organizations realize by implementing process mining?*; and (2) *Which socio-technical antecedents lead to realization of these value potentials?*

Towards this end, we conduct an assessing literature review, according to Leidner (2018), to systematically search and code the literature to provide a synthesis of trends or gaps. As a theoretical organizing device (Leidner, 2018), we draw on the IT artifact within its nomological net (Benbasat and Zmud, 2003). The nomological net defines the interlocking system of laws through which a phenomenon occurs (Cronbach and Meehl, 1955). Therefore, to investigate the phenomenon of interest, i.e., organizational value realization enabled by process mining, it is essential to understand the components and interrelations of the nomological net in which it occurs (Cronbach and Meehl, 1955). By contextualizing the process mining artifact within its nomological net, the assessing literature review (Leidner, 2018) synthesizes the findings of 58 empirical studies to discuss socio-technical practices and capabilities necessary for and business values enabled by process mining in organizations.

Our results contribute to research twofold. First, we contribute to the still limited understanding of what type of business values are enabled by leveraging BDA IT artifacts and what are the underlying socio-technical conditions that lead to value realization (Abbasi et al., 2016). Second, we add an organizational perspective to the research on process mining that – despite the technology's increasing practical relevance (Kerremans, 2019)—is instead focused on algorithms (Wang et al., 2012) and tool development (Turner et al., 2012) than on practical implications for organizations. These results serve as a starting point for practitioners to reflect on the purpose and necessary conditions for successfully leveraging business value from using process mining in organizations.

## 2 Theoretical Background

### 2.1 Process Mining

Process mining is rooted in constructing process models based on how business processes are executed in a specific context rather than designing them based on theoretical considerations (van der Aalst and Weijters, 2004). A business process defines how “*resources of an enterprise are used*” (Agrawal et al., 1998, 469). Because of the direct impact on organizations’ performance, there has long been the question of how organizations are carrying out business processes. Agrawal et al. (1998) introduced the concept of automatically constructing process models from event logs of past executions of a process to address this problem. Since then, process mining has emerged as a technology to discover, monitor, and improve real business processes in a variety of application domains (Song and Van der Aalst, 2008, van der Aalst, 2011).

The multitudes of event data logged in information systems provide the basis for process mining (van der Aalst, 2011). The challenge for an organization is then to derive meaningful insights from these data to generate findings on process execution, discover problems of process performance, and improve the way their business operates (Song and Van der Aalst, 2008). Process mining aims to do this by leveraging event logs that comprise sequentially recorded events, where each event relates to a specific activity. These activities make up well-defined steps in a business process. Additional information, such as the person or system executing the activity, the costs related to the activity, and the timestamp of the activity, may also be available for analysis (van der Aalst, 2011).

Based on the event log, three types of process mining are possible. First, process discovery allows organizations to derive a process model that reflects the actual behavior recorded in the event log, even not knowing the process beforehand. Second, organizations can use conformance checking to compare a priori process models to the event log of the same process. Thus, firms can detect deviations of the real process from the target process (van der Aalst, 2011). Third, process enhancement helps organizations to focus on improving an existing process model based on information in the corresponding event log about the actual process. Therefore, a priori process models can be aligned to encompass certain specialties of the real process (van der Aalst, 2011).

Thus far, research on process mining has focused mainly on developing algorithms for process discovery (Ailenei et al., 2011). For example, van Dongen et al. (2009), Wang et al. (2012), and Rubin et al. (2007) provide comprehensive reviews on process mining algorithms. Furthermore, Turner et al. (2012) give an overview of process mining tools. More recently, there is a growing body of literature that recognizes the application of process mining in an organizational context. However, most of the research has been descriptive and confined to the technological facets of applying process mining in organizations. As a large share of process mining research is concerned with the implementation in a healthcare context, Rojas et al. (2016) provide an overview of the field to guide researchers when applying process mining in a healthcare context. These insights are extended by Ghasemi and Amyot (2016), analyzing the volume of research at the intersection of process mining and healthcare, and context-specific literature reviews on the applicability of process mining in oncology (Kurniati et al., 2016) and frail elderly care (Farid et al., 2019). Even though these reviews provide valuable insights on the feasibility of implementing process mining in healthcare research, the results are restricted to the technological perspective, focusing on process mining types, tools, algorithms, data sources, implementation strategies and technical challenges. Similar literature reviews can be found with a focus on process mining algorithms, tools, and methods for e-learning (Ghazal et al., 2017) and for end-to-end processes in supply chain management (Jokonowo et al., 2018). Acknowledging the diverse application scenarios for process mining in practice, the literature studies of Thiede et al. (2018) and Dakic et al. (2018) are a first step to investigate industry sectors and processes that process mining has been implemented for in empirical studies, with a focus on prevailing data sources, process mining types and tools. In conclusion, we observe a growing interest in studying the organizational application of process mining, yet, literature reviews to date have tended to focus on technological practices and

challenges for applying process mining rather than on its socio-technical implications and organizational benefits. Thus, it remains unclear what socio-technical antecedents and mechanisms lead to business value realization enabled by process mining and how business values manifest.

## 2.2 Business Value Realization from IT

Scholars have long discussed how the implementation of IT within organizations leads to IT business value realization (Melville et al., 2004). IT business value is defined as “*the organizational performance impacts of information technology at both the intermediate process level and the organization-wide level, and comprising both efficiency impacts and competitive impacts*” (Melville et al., 2004, 287). To this end, research has mostly focused on two fields: mediating factors that impact how IT investments turn into IT-based value, such as IT-strategy alignment and organizational capabilities (Kohli and Grover, 2008) and how these IT-based values manifest (Schryen, 2010). Still, the precise mechanisms to realize business value from IT and the influence and interrelation of antecedents, such as the technological, personnel, or industry context, remain unclear (Melville et al., 2004, Schryen, 2010).

Taking into account the influence of the BDA paradigm shift, Grover et al. (2018) extend the literature on value realization from IT to encompass value realization from BDA. However, questions concerning what paths lead to value creation, how to develop appropriate BDA capabilities and practices, and how to assess the impact of BDA remain unanswered (Grover et al., 2018). These questions are of critical importance for IS research considering how BDA is changing the organizational information value chain to encompass new technologies, roles, and skills (Abbasi et al., 2016). For instance, the emergence of novel BDA IT artifacts, such as process mining analyses, requires data scientists to develop new skills in data integration, preparation, analysis, and interpretation to support real-time data-driven insights (Abbasi et al., 2016). Such insights from process mining result in diverse business values, ranging from shortening production times through transparency on bottlenecks (Lee et al., 2014) to improved customer satisfaction through enhanced service quality by uncovering neglected but essential process steps in customer care (Edgington et al., 2010). Those examples illustrate how BDA is impacting and impacted by the embedded organizational context.

To understand the interplay between the IT artifact and its organizational context, Benbasat and Zmud (2003) call for IS research to study the IT artifact within its immediate nomological net. The immediate nomological net comprises (1) the IT artifact, which is defined as “*the application of IT to enable or support some task(s) embedded within a structure(s) that itself is embedded within a context(s).*” This rich organizational context manifests itself in (2) organizational capabilities and practices that comprise “*the managerial, methodological and technological capabilities as well as the managerial, methodological, and operational practices involved in planning, designing, constructing, and implementing IT artifacts*” (Benbasat and Zmud, 2003, 186). Resulting from (3) its use in the organizational context, the IT artifact (4) impacts “*the humans who directly (and indirectly) interact with them, structures and contexts within which they are embedded, and associated collectives (groups, work units, organizations)*” (Benbasat and Zmud, 2003, 186). By investigating the IT artifact within its immediate nomological net, IS research strives to understand the socio-technical antecedents and processes that enable organizations to implement IT and realize value from its use (Benbasat and Zmud, 2003).

## 3 Design of the Literature Review

We conducted an assessing literature review, according to Leidner (2018). We chose this type of literature review as it is suitable for synthesizing current trends and gaps in a research stream by systematically coding the extant literature according to a pre-defined theoretical framework (Leidner, 2018). This approach enables us to rigorously identify what is known and unknown about the antecedents and impacts of process mining usage in organizational settings through contextualizing process mining as an IT artifact within its immediate nomological net (Benbasat and Zmud, 2003).

### 3.1 Sampling

Following the systematic literature search process of Webster and Watson (2002), we screened relevant outlets and looked for publications that (a) focus on organizational usage of process mining and (b) include an empirical study on implementing the use case. Subsequently, we coded the studies based on the dimensions of the nomological net surrounding process mining. We used the leading Information Systems (IS) journals included in the Association for Information Systems (AIS) Senior Scholars' Basket of A-rated IS journals (Association for Information Systems, 2011) as the starting point for finding relevant literature. We expected the publication of relevant articles on process mining in an organizational context in these leading IS journals. To further the organizational perspective on process mining, we also included the Financial Times 50 (FT50) journal list (Ormans, 2016). To enrich the data set with contemporary studies, we included the proceedings of the International Conference on Information Systems (ICIS) and the European Conference on Information Systems (ECIS) as the top IS conferences. Since process mining has its roots in computer science research, we included the top five journals from the AIS special interest group on Decision Support and Analytics as we expected them to add to the technical perspective on process mining. To deepen the technical perspective, we included IEEE Access, IEEE Transactions on Services Computing, IEEE Transactions on Knowledge and Data Engineering, and the Communications of the ACM, as these outlets publish research on process mining regularly. Finally, we included the proceedings of Business Process Management Workshops (BPMW) and the Business Process Management Journal since process mining is deeply related to business process management research.

| Outlet   | Initial search                                      |          | FW/BW    |    |
|--|---|----------|----------|----|
|  | Hits  | Selected | Selected |    |
| Senior scholars' basket and FT 50                | European Journal of Information Systems             | 1        | 0        | -  |
|  | Information Systems Research                        | 1        | 0        | -  |
|  | MIS Quarterly                                       | 3        | 0        | -  |
|  | INFORMS Journal on Computing                        | 1        | 0        | -  |
|  | The Accounting Review                               | 2        | 1        | -  |
|  | Organization Science                                | 2        | 0        | -  |
|  | Production and Operations Management                | 1        | 0        | -  |
| AIS SIG  | Decision Support Systems                            | 16       | 4        | -  |
|  | Expert Systems with Applications                    | 26       | 8        | -  |
|  | Information Systems Frontiers                       | 4        | 2        | -  |
| AIS conf.  | ICIS  | 26       | 0        | -  |
|  | ECIS  | 52       | 4        | -  |
| Process mining-relevant conferences and journals | BPMW  | 389      | 7        | -  |
|  | Communications of the ACM                           | 1        | 0        | -  |
|  | IEEE Transactions on Knowledge and Data Engineering | 9        | 0        | -  |
|  | IEEE Access   | 15       | 2        | -  |
|  | IEEE Transactions on Services Computing             | 19       | 1        | -  |
|  | Business Process Management Journal                 | 32       | 1        | -  |
| Other  | Other journals                                      | 100      | 15       | -  |
|  | Other journals                                      | -        | -        | 12 |
|  | Other conferences                                   | -        | -        | 1  |
|  |   | 700      | 45       | 13 |

Table 1. Summary of the literature search process.

### 3.2 Data Collection

As a first step, we deployed a keyword search for “process mining” in title, abstract, and keywords without temporal limitation on Scopus, Web of Science, AIS e-Library and IEEEExplore, restricting the search to the previously identified relevant outlets. The initial search revealed 700 hits. Next, we analyzed the articles regarding their title and abstract to reveal their importance for understanding value realization enabled by process mining. We only included articles with an empirical study where the authors investigated the application of process mining for an organizational use case. This process yielded 45 articles, which we supplemented through a forward and backward search (Webster and

Watson, 2002). The backward search resulted in an additional six articles, and the forward search resulted in an additional seven articles. In sum, the final set comprised 58 research articles published between 2005 and 2019 (see Table 1). We attached the complete list of included articles in the reference section and marked them with an asterisk.

### 3.3 Analysis

Following Leidner (2018), we use the nomological net surrounding process mining (Benbasat and Zmud, 2003) as a theoretical framework to guide the coding process. To conduct the literature coding, we followed a grounded theory coding process (Glaser and Strauss, 1967). This approach comprises open coding of first-order concepts from the literature that describe the phenomenon of interest, i.e., value realization enabled by process mining in organizations. Then, we formed second-order constructs in the process of axial coding to establish relationships between the codes. In the last step, we conducted selective coding to aggregate dimensions that describe relating second-order constructs (Gioia et al., 2013). As we contextualize organizations' use of process mining as an IT artifact within its nomological net, we followed an abductive approach. In this approach, we used the dimensions of the nomological net as selective codes and conducted the open and axial coding inductively based on the selected papers. Starting with open coding, we used a line-by-line coding approach to extract quotes that relate to the antecedents for and value generation enabled by process mining. We then categorized the resulting 169 first-order codes into 47 second-order themes that comprise relationships (Gioia et al., 2013). For instance, we discovered that through process mining firms obtain, among others, *transparency on frequent process flows*, *transparency on anomalous process flows*, and *transparency on employee interaction*. We then summarized these first-order concepts under the second-order theme *transparency*. In the last step, we matched the derived 47 second-order themes to the four dimensions of the nomological net that served as aggregate dimensions. In case a second-order theme could not be related to one dimension, we excluded it from further analysis to strengthen our focus on the nomological net. For example, we abandoned the theme *industry* as we discovered that as part of the organization's technological capabilities, the source system providing the data for the process mining analysis is mirroring the process and the respective industry. Similarly, we dropped the theme *challenges* as these turned out to manifest in the nomological net as part of the process mining artifact and technological capabilities of the firm. In sum, we obtained four aggregate dimensions that reflect the contextualized nomological net for process mining as an IT artifact implemented and used by organizations.

## 4 Results

We describe the results from our literature review along the dimensions of the nomological net (Benbasat and Zmud, 2003) surrounding the process mining artifact. The (1) process mining IT artifact is (2) used by organizations and embedded within an organizational context that comprises (3) specific organizational capabilities and practices that are necessary to design and implement the process mining analysis, so the organization can (4) realize business value potentials from its use (see Figure 1). As our analysis focuses on explicating the dimensions of the nomological net around process mining, the arrows in Figure 1 show exemplary relationships that we further elaborate on as avenues for future research.

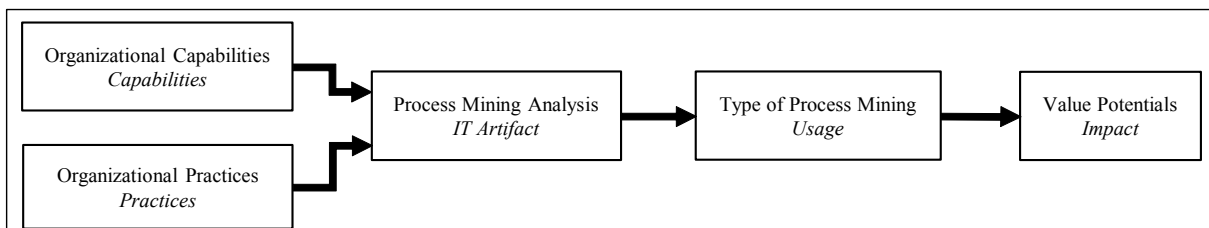


Figure 1. Process mining as IT artifact within its nomological net (based on Benbasat and Zmud 2003).

## 4.1 Process Mining as an IT Artifact

Governing the evolving lifecycle of the process mining artifact is a challenge that researchers are addressing with various implementation procedures, such as the L\* lifecycle model (van der Aalst et al., 2011) or the Process Diagnostics method (Bozkaya et al., 2009). These procedures support firms in executing the different stages of a process mining project, from understanding the goal of the analyses over extracting and preparing data to create process models and interpreting the results (van der Aalst et al., 2011).

Such implementation procedures revolve around the process mining analysis as an IT artifact at the center of the implementation project. We observe three specific characteristics that distinguish process mining from other IT implementations. First, the plethora of available mining algorithms urges organizations to familiarize themselves with available methods and select the appropriate algorithm regarding the data quality and process analysis goals (van der Aalst, 2011). Widely adopted algorithms (Erdogan and Tarhan, 2018, De Weerd et al., 2012b), are complemented by highly specialized algorithms that scholars can adapt to a specific problem context (Breuker et al., 2016).

Second, the results indicate that the selection of a suitable algorithm relates tightly to the underlying data quality. The impact and success of process mining in an organization depend on the availability and quality of event data that represent a process flow (Knoll et al., 2019). These data may be distributed in different formats and granularity intra-organizationally across various systems or even inter-organizationally across different firms (Quaglini, 2008). Obtaining, pre-processing, and merging these data, especially regarding incomplete (Leyer and Moormann, 2015) or outlier-prone event logs (Märüşter and van Beest, 2009), poses hurdles that organizations need to overcome to implement valuable process mining artifacts (van der Aalst et al., 2011).

Third, valuable process mining artifacts also depend on the design of the process mining analysis. As process mining can display process flows as maps, organizations need to decide on the perspective and level of granularity that such a process map should provide (Partington et al., 2015). While an auditor may be interested in highly detailed visualizations of individual process flows to detect fraudulent behavior (Jans et al., 2014, Baader and Krcmar, 2018), users from management-level may rather be intrigued by the aggregating analysis of costs related to specific process steps (Ceglowski et al., 2005). This example illustrates that the design of the process mining analysis is strongly influenced by the intended usage of the IT artifact.

## 4.2 Usage of the Process Mining Artifact

The majority of research focuses on how organizations **discover as-is business processes** (Ho et al., 2009, De Weerd et al., 2012a), either by discovering process models (Baader and Krcmar, 2018, De Leoni et al., 2016) or interaction models (Alvarez et al., 2018, Stuit and Wortmann, 2012). With regards to the chosen mining algorithm, the discovered process model can display different levels of complexity, from a static view of the behavior found in the event log to an analysis of more or less frequent paths (Jans et al., 2014, van der Aalst, 2011). This extension of process discovery allows for the **analysis of different variants** of the same process. Organizations can draw on these insights to reflect on the complexity and diversity of business processes. A typical use of process discovery is the application in hospitals where, despite a highly regulated environment, patients with diverse needs require individual treatment flows (Zhou and Piramuthu, 2010).

The understanding of actual process flows furthered by using **conformance checking** to detect deviations from standard process models (Bozkaya et al., 2009, He et al., 2019, Li et al., 2011). Once deviations are known and assessed, organizations can leverage this knowledge to enhance the existing process models to be more appropriate and comprehensive, a process mining technique known as **process enhancement** (Li et al., 2011).

As process mining creates transparency on process flows, organizations use it to **assess the performance** of business processes. Process performance is typically measured in throughput times, which is reflected in the time required to perform a process (Bozkaya et al., 2009, Rebuge and Ferreira, 2012), the number of bottlenecks such as activities delaying the process (De Leoni et al., 2016) or process loops in the form of repeated execution of activity patterns (van der Aalst et al., 2007, Mărușter and van Beest, 2009). To gain more accurate results, scholars started to combine process mining and data mining techniques, such as decision and regression trees, to derive predictions of how particular process characteristics will influence the process outcome (De Leoni et al., 2016). These **predictions** can inform measures to intervene on process flows that will probably lead to reduced quality output.

### **4.3 Organizational Capabilities and Practices**

Successfully implementing process mining projects in an organizational context implies organizational capabilities and practices as antecedents to value realization. Based on the literature, we found only one study focused on organizational success factors for implementing process mining, derived from the literature on process modeling (Mans et al., 2013a).

First, **organizational capabilities** are a crucial requirement for process mining project success, which are reflected in the organizational context as well as the data and system context. The organizational context comprises general project-related factors, such as the capability of the company's senior management to support the process mining initiative and the availability of resources to execute the project (Mans et al., 2013a). Besides, we also observe the relevance of process mining-specific factors that extend to the data and system context. The availability and quality of raw data and the constructed event logs are critical antecedents to successful process mining (Mans et al., 2013a, Knoll et al., 2019). Depending on the industry and process under consideration, different information systems serve as a source for the event data. That is the reason we observe a high fragmentation of source systems in the literature. With a clear emphasis on studies of clinical pathways in the healthcare sector (36%), the dominant source systems are Hospital Information Systems and the Electronic Health Record (combined 21%) that provide structured information on patient treatments and medical workflows (Alvarez et al., 2018, Rojas and Capurro, 2019). As 22% of the studies investigate core business processes, such as Purchase-to-Pay (Baader and Kremer, 2018, van der Aalst et al., 2007) or Order-to-Cash (Fleig et al., 2018, Mărușter and van Beest, 2009), Enterprise Resource Planning systems and Workflow Management Systems provide a frequent source of rich event data. Both systems usually yield highly structured and detailed event data (van der Aalst et al., 2011) that can be pre-processed rather effortlessly, e.g., through standardized SQL scripts (Fleig et al., 2018). In contrast, process mining has also been applied to specialized systems (Brunk et al., 2018, Zerbino et al., 2018) or to manually collected data, for instance, observer-based data of surgical procedures (Lira et al., 2019). These data, however, are often ambiguous and incomplete and thus require extensive expert knowledge for pre-processing so that chronological, concise event logs can be produced (He et al., 2019).

Second, **organizational practices** need to be in place to foster the implementation and usage of process mining. The process mining implementation requires a structured procedure and project management and the availability of analytical expertise to prepare and conduct the process mining analysis (Roldán et al., 2018, Mans et al., 2013a). This procedure includes strategies to collect event data, the careful selection of suitable process mining algorithms given the problem at hand (Mans et al., 2013a), and the focus on relevant areas of analysis (Partington et al., 2015). Furthermore, the discussion with project stakeholders and process owners, which we found to be a crucial practice for realizing meaningful process mining projects, influences this process. The main goal of discussion between stakeholders is to validate the quality of raw data and the interpretation of analysis results (Alvarez et al., 2018, Zerbino et al., 2018), which encompasses the distinction between wanted and unwanted deviating behavior (Bozkaya et al., 2009, Helbig et al., 2016) and interpreting root causes for process variances (Fernández-Llatas et al., 2013, Wang et al., 2014) and the estimation of severity in case of non-conformance to specific process standards (Zerbino et al., 2018). Thereby, the discourse of stakehold-

ers enables faster identification of meaningful results (van der Aalst et al., 2007). How the analysis results are presented and communicated to the project stakeholders shapes the way the following discussion and use of the results unfolds (Cho et al., 2017). Presenting the resulting process models in an interactive rather than static or descriptive manner may ease the interpretation for organizational stakeholders (Bozkaya et al., 2009).

#### **4.4 Organizational Impact**

With a research focus on the control-flow of processes, 74% of studies focus on the **transparency** of process flows as a significant value of process mining. Process mining allows uncovering the execution of processes in a specific context and can yield insights on the most frequent process flows as well as on infrequent or anomalous flows. Drawing on this characteristic, firms can create a model of how a particular process is executed, which can then be used to uncover anomalous, fraudulent executions that lack specific process steps (Jans et al., 2014). Those insights serve as input for the auditor to detect fraud comprehensively much earlier in the audit compared to traditional techniques that focus on random tests of internal control mechanisms (Jans et al., 2011). Process mining-enabled transparency also extends to the organizational perspective, as it generates transparency on organizational structures that manifest in employee roles and allocation. Organizations use process mining to construct models representing the interaction of employees, giving insights on how employees are allocated and how they collaborate. As a result, firms can identify employees suffering from high workload (Pika et al., 2017) or detect inefficient interaction patterns, for example, in emergency departments where efficient collaboration is vital (Alvarez et al., 2018, Mans et al., 2008). Process mining also enables transparency in customer behavior. Shopping malls use this transparency to discover customer paths in their malls based on a Bluetooth-based positioning system (Dogan et al., 2019), or healthcare institutions get insights of sudden changes in behavioral patterns of seniors at risk of suffering from dementia episodes (Fernández-Llatas et al., 2013).

Based on process mining-induced transparency, the studies show a clear tendency to measure process **performance** and to increase process **efficiency**. For example, process mining is used to find root causes for long cycle times in service processes in the financial industry, so that after identifying bottlenecks, alternative, faster workflows can be proposed, which leads to increased efficiency that can be estimated through simulation models (Leyer and Moormann, 2015). Analyzing the suppliers' lead time in a production process, Lau et al. (2009) enrich these performance data with additional production information and derive association rules on how these parameters influence the product quality. The combination of process mining with diverse analysis techniques, such as association rule mining (Lee et al., 2014), simulation models (Cho et al., 2019), or clustering techniques (Lee et al., 2013), is notable. Combining analysis techniques allows expanding the capabilities of process mining to not only analyze the process and its immediate context but also to correlate different process characteristics (De Leoni et al., 2016) and estimate their impact on, among others, product quality (Lau et al., 2009), human behavior (Brunk et al., 2018) or customer satisfaction (Ho et al., 2009).

Enterprises must ensure the **conformance** of their processes to regulatory requirements and internal workflow standards. Conformance is due to both an increase in external, regulatory requirements, such as the Sarbanes-Oxley Act (SOX), and the need for organizations to align their processes to support quickly changing business requirements optimally (van der Aalst, 2011). To this end, process mining allows the analysis of conformance of a real process with the desired process model to detect any deviations (Rebuge and Ferreira, 2012). This type of process mining also enables companies to generate automated recommendations on a suitable standard process model to reduce the overall costs of **standardization** (Fleig et al., 2018).

Process mining allows for a fact-based implementation and **monitoring of organizational change**, facilitated by the ability to gain transparency on process flows and measure process performance. To this end, scholars employ process mining to validate the effects of business process reengineering projects, yielding results on time savings and cost increases related to different reengineering measures

(Cho et al., 2017). **Forecasting** the effects of organizational changes by process mining allows decision-makers to make more informed decisions on change projects while decreasing the effort for data generation and analysis (Alvarez et al., 2018, Roldán et al., 2018).

## 5 Discussion, Limitation, and Conclusion

It is inherent to the IS discipline to deepen the understanding of how elements of the nomological net are interconnected, to understand how IT artifacts are constructed, implemented, and used, and how they impact the context they are embedded in (Benbasat and Zmud, 2003). Building on the dimensions around the process mining artifact in organizations that resulted from our literature review, we now turn to relationships between the elements to illustrate fruitful areas for future research.

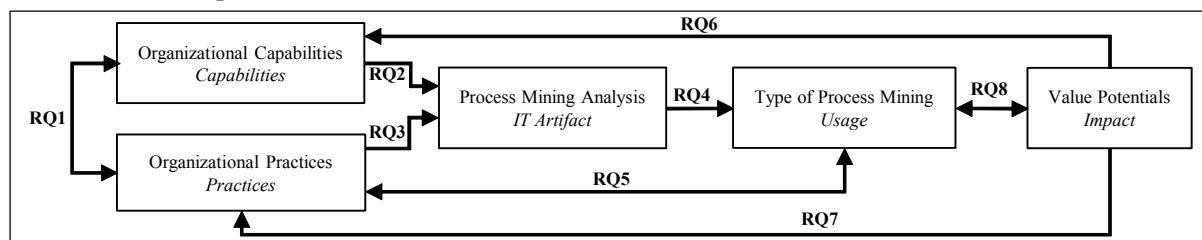


Figure 2. Potential research questions related to process mining within its nomological net.

### 5.1 Developing Antecedents for Process Mining

Even though the realization of value potentials enabled by process mining requires specific organizational capabilities and practices (Mans et al., 2013a), there is sparse knowledge of **how these antecedents are developed**. First, we turn to the **interplay of organizational capabilities and practices** as antecedents for implementing and using process mining. We expect **organizational practices** to influence the development of technological capabilities for process mining. An example is the influence of IT governance practices on the provision of data necessary for process mining. IT governance provides rules that imply “*which department makes what IT decisions*” (Tiwana and Kim, 2015, 656), including decisions on what, for example, structured and unstructured, and how, for example, centralized or decentralized, data will be stored (Weill and Ross, 2004). Storing and handling data in a centralized or decentralized approach defines whether processes can interlink business units end-to-end in a standardized way or are highly diversified for each business unit (Weill and Ross, 2004). We call for researchers to investigate how managerial practices, such as IT governance mechanisms, are facilitating or hindering the exploitation of process mining, thus, contributing to the debate on the interplay of BDA and organizational culture (Abbasi et al., 2016).

In turn, also organizational practices to implement and use process mining will vary depending on the **organization’s capabilities** in data storage and provision. Applying process mining to highly regulated production processes may require different practices in data pre-processing, analysis design, and usage than the implementation for flexible, human-centric processes. While production processes usually provide large amounts of detailed, structured log data (Mans et al., 2013a), human-centric, behavioral processes are often not digitally tracked, evolve and, in contrast to most business processes, do not provide clear precedence among activities (Fernández-Llatas et al., 2013). Organizations are then challenged to develop data collection and analysis practices to cope with incomplete and unstructured data sets. These newly established practices can be iterative and agile as an incremental identification, and analysis of distributed process data in collaboration with diverse stakeholders becomes necessary (Pika et al., 2017). In addition, processes with critical effects, for example, on human lives, require different practices in data analysis and change implementation. Analyzing and optimizing the performance of hospital emergency room episodes has a direct impact on human lives (Rojas et al., 2019), thus requiring a careful ex-ante validation of patient data and ex-post discussion of analysis results. In contrast, the continuous monitoring to improve production processes requires a thorough ex-ante dis-

cussion with stakeholders to develop a shared understanding of process characteristics relevant for long-term analysis (Lee et al., 2014). In conclusion, we encourage researchers to investigate these interdependencies to shed light on how firms need to adapt their organizational practices and technological capabilities when implementing BDA. We therefore pose **RQ1: What are reciprocal effects between organizational practices and technological capabilities as antecedents for process mining?**

## 5.2 Implementing Process Mining

Even though firms draw on organizational practices and capabilities to **implement the process mining artifact**, to the best of our knowledge, it is not fully understood how these antecedents affect the design and implementation of process mining in organizations. Most studies in the process mining literature examine the design and implementation of process mining artifacts from the viewpoint of the researcher who seeks to adapt and implement the technology for a novel use case. Despite valuable insights on opportunities for process mining resulting from this approach, we consider it crucial to acknowledge the perspective of organizational users, who are ultimately shaping the design and usage of process mining based on their expertise (Mans et al., 2013a). Different degrees of **analytical and decision-making capabilities** influence how users derive and act upon insights from process mining. Certain features, such as an initial process discovery enabled by plugin modules in process mining tools (Bozkaya et al., 2009), are easy to implement and understand for users with limited analytical expertise. Other analysis types, such as a process model validation and enhancement, potentially deliver more profound insights but require expert knowledge in implementation and interpretation (Roldán et al., 2018). This ambiguity raises the question of who needs what information in which format at what time to make decisions. A senior manager may be interested in a high-level analysis of resource allocation and performance to estimate overall improvement potentials (Fleig et al., 2018), while a process owner may want to analyze production process performance depending on specific machine settings or process operators (Ho et al., 2009). We, therefore, encourage scholars to focus on how these capabilities impact the design and usage of process mining artifacts that enable different types and levels of analysis and how these lead to different business values: **RQ2: How are users' analytical and decision-making capabilities impacting the design and use of process mining artifacts?**

While it is essential to address questions about capabilities on an individual level, it is equally important to acknowledge the group level. Creating a shared mindset among employees and establishing **collaborative practices** is essential for firms striving to successfully leverage BDA (Dremel et al., 2017). The importance of such practices becomes clear when thinking of the technical and social demands that process mining poses for an organization. On the one hand, process data may be distributed in varying formats and quality across several departments and IT systems (Ho et al., 2009). On the other hand, diverse stakeholders – ranging from IT specialists to process owners and operators to data scientists – have distributed knowledge on technologies and processes that is critical to the success of process mining (Zerbino et al., 2018). While we expect collaboration across departments, roles, and systems to positively influence the implementation and usage of process mining artifacts in organizations, we consider it necessary to investigate what collaborative practices have an exceptionally high impact on process mining implementation and usage and how those can be established: **RQ3: What collaboration practices influence the implementation and usage of process mining artifacts?**

## 5.3 Using Process Mining

How a firm **uses process mining** depends on one hand on the process mining artifact itself. Foremost, the **design and implementation of the process mining artifact** will impact how users adopt the technology. Users' intention to employ the technology will likely increase when their needs and expectations towards the technology are met (Venkatesh et al., 2003). Technology acceptance has long been studied in IS research, leading to a variety of models that have also been adapted to the BDA context (Verma et al., 2018, Gunasekaran et al., 2017). In the realm of BDA, factors such as information quality and quality of information processing become salient for technology acceptance (Verma et al.,

2018), as the overarching goal of system usage shifts to exploring data and deriving knowledge (Marchand and Peppard, 2013). We expect these BDA-specific factors to be crucial for process mining. However, research has not addressed if existing BDA technology acceptance models hold for process mining and whether and which characteristics of the process mining artifact differentiate it from other BDA technologies. We, therefore, propose **RQ4: How are characteristics of the process mining artifact impacting the intention to use the technology?**

On the other hand, the use of process mining is influenced by **organizational practices**. Process mining increases transparency on the organization's business processes. However, the process of collecting and preparing the necessary data basis may often remain invisible to the broader public as it is executed automatically in the underlying IS (Jans et al., 2014). Richards and King (2013) sound a cautionary note on this transparency paradox and call for BDA leaders to acknowledge this ambiguity by developing mechanisms that inform the people impacted by BDA on how data are collected and how insights are derived (Richards and King, 2013). Thus, we encourage researchers to remember that process mining is a powerful tool with the potential to analyze the workflows of individual human beings in almost unlimited detail. With this power, **ethical considerations** on process mining become paramount. We see the need to extend the currently technologically-driven research on process mining also to include ethical questions on collecting, preparing, and analyzing process data for individuals and organizations that use and are influenced by process mining, as summarized in **RQ5: What are the reciprocal effects between ethical considerations and the usage of process mining artifacts?**

#### 5.4 Realizing Value from Process Mining

Our results suggest that the organizational use of process mining enables a multitude of value potentials, ranging from workload transparency to improved process performance to monitoring organizational change initiatives. However, these outcomes are not an end in themselves, but in turn, have reinforcing effects on future value realization from process mining. First, we propose that realized value potentials have an amplifying impact on the **development of technological capabilities**. An example is the organization's capability to provide reliable data to reconstruct event logs. There is consensus that reliable data is the most crucial antecedent to the meaningful implementation of process mining (van der Aalst and Weijters, 2004). However, research shows that data availability is an ongoing challenge in process mining since firms struggle to obtain and pre-process suitable data (Kerremans, 2019, van der Aalst et al., 2011). One way to improve data quality may be the use of initial process mining analysis to discover that essential processes are not tracked in the IS (Jans et al., 2014). This approach may lead to changes in the underlying IS or the development of new tracking capabilities, such as implementing RFID (Lee et al., 2014), to enable more detailed process mining analyses that potentially lead to deeper insights. Even though implementing process mining may face technological difficulties in the early stages, reinforcing mechanisms make long-term value potentials transparent. Hence, we aim to contribute to the debate on BDA value creation mechanisms, particularly considering data availability issues (Abbasi et al., 2016, Grover et al., 2018) through **RQ6: How do realized value potentials influence the enhancement of technological antecedents for process mining?**

Second, we expect values realized from process mining to impact the further **development of organizational practices**, for instance, process-oriented business practices. Research has long acknowledged that in today's fierce competition, organizations are coerced to shift their focus from governing business functions to holistic design and governance practices of end-to-end business processes (Kim et al., 2011). Even though organizational process-orientation is known to lead to benefits such as improvement of customer satisfaction and financial performance (Kohlbacher, 2010), organizations face challenges during implementation in practice. Process-orientation imposes high demands on organizations to govern such end-to-end processes (Willaert et al., 2007) and to implement desired process changes in practice (Jurisch et al., 2016). We expect process mining to facilitate the establishment of process-oriented organizational practices. One reason is that process mining has been reported to foster transparency on end-to-end processes (Özdağoğlu et al., 2019) and facilitate monitoring of business process reengineering projects (Cho et al., 2017) which are fundamentals of process-oriented organiza-

tional practices. The other reason is that obtaining and acting upon results from process mining is also known to enhance the “*process-oriented thinking*” of employees (Fleig et al., 2018, 240) by making them aware of how business processes are executed and interlinked in reality. Consequently, we encourage scholars to further deepen our understanding of how process mining is acting as facilitator for process-oriented practices that acts as enabler for value realization: **RQ7: How do realized value potentials influence the establishment of process-oriented organizational practices?**

Third, we propose that the use of process mining will impact the **transition towards data-driven decision-making processes**. Consider, for example, that workflows that were once considered optimally designed and flawless now become transparent in their actual execution and performance through process mining (Fleig et al., 2018). This means that processes and behaviors that used to be hidden now become transparent through data-driven analysis, and executives can take actions based on these objective insights, which opens up new avenues for value creation. However, this newly introduced data-driven transparency replaces previous decision processes that were based on expert assessments or personal hunches. An arising tension between data-driven implications of the analysis and the intuition-based recommendations of the experts is the result. This tension fuels some of the most urgent questions of BDA research, i.e., the way organizations “*transform from an intuition-based decision-making culture to a data-driven decision-making culture*” and how to establish the ideal balance between data and intuition (Abbasi et al., 2016, xiii). We, therefore, encourage future longitudinal studies to shed light on how novel analytics technologies are transforming decision-making culture in organizations, as summarized in **RQ8: How is the organizational usage of process mining impacting the transition from intuition-based decision-making to data-driven decision-making?**

| Theme                       | Research Question  |
|-----------------------------|--|
| Developing Antecedents      | <b>RQ1:</b> What are reciprocal effects between organizational practices and technological capabilities as antecedents for process mining?   |
| Implementing Process Mining | <b>RQ2:</b> How are users’ analytical and decision-making capabilities impacting the design and use of process mining artifacts?<br><b>RQ3:</b> What collaboration practices influence the implementation and usage of process mining artifacts?   |
| Using Process Mining        | <b>RQ4:</b> How are characteristics of the process mining artifact impacting the intention to use the technology?<br><b>RQ5:</b> What are the reciprocal effects between ethical considerations and the usage of process mining artifacts?   |
| Realizing Value             | <b>RQ6:</b> How do realized value potentials influence the enhancement of technological antecedents for process mining?<br><b>RQ7:</b> How do realized value potentials influence the establishment of process-oriented organizational practices?<br><b>RQ8:</b> How is the organizational usage of process mining impacting the transition from intuition-based decision-making to data-driven decision-making? |

Table 2. Questions to guide future research on process mining.

Table 2 summarizes the questions that we consider fruitful avenues for future research on process mining in its socio-technical context. However, we recognize that our review is subject to several **limitations**. First, by adopting the method of an assessing literature review (Leidner, 2018), we drew on the theory of the IT artifact in its nomological net (Benbasat and Zmud, 2003) to guide our analysis. Even though we consider this a valuable framework close to the core of the IS discipline to study the construction process and impact of IT in organizations, other more specific theoretical frameworks, such as the BDA value creation framework (Grover et al., 2018), may inform different insights outside the nomological net around process mining. Second, we ground our analysis in the results of 58 empirical studies on the organizational use of process mining that span a diverse field of application scenarios. Even though this allowed us to derive various antecedents for and value potentials enabled by process mining and to identify open questions on the underlying mechanisms that still need to be answered, we acknowledge the need for further expanding our understanding of hitherto unknown values and mechanisms in practice by, for example, acquiring longitudinal data through multiple case studies.

As organizations are challenged to adapt their processes to quickly changing business requirements, the potential of Big Data-driven insights enabled by process mining becomes increasingly valuable. However, practitioners still fail to leverage the potential benefits of process mining. Toward this end, this study puts process mining in its organizational context represented by the nomological net. This broadens our understanding of the interplay between process mining and the realization of value in organizations. Furthermore, we depict a research agenda of how organizations develop the antecedents necessary to implement process mining and how lasting business value can be created.

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(\* result of the literature review process)

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