Structuring Empirical Research on Process Mining at the Individual Level using the Theory of Effective Use

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Abstract. A growing number of empirical papers on the topic of process mining has been published in years. After a first wave of contributions on application scenarios, there has been a second wave aiming to establish theoretical insights into how process mining tools are used and how benefits unfold from this usage. Many of these papers follow an explorative, qualitative, or inductive approach. A weakness of these contributions is their theoretical cohesion and integration. This paper makes an effort to integrate into a more holistic theory that can eventually provide a foundation for more deductive and quantitative empirical research on process mining. To this end, we build on the theory of effective use and focus on the individual effect on decision makers. We find opportunities for revision and refinement of this theory for process mining. Specifically, we discuss moving from constructs on learning to expertise, and integrating a pragmatic perspective that complements the semantic emphasis of representational fidelity.

Keywords: Process Mining · Theory of Effective Use · Empirical Research.

1 Introduction

Recent years have seen process mining developing from a research domain to a category of commercial enterprise software with an increasing uptake in industry [11]. The growing usage in practice has also confronted process mining researchers with new research questions that shift from the technical level to the user level and the organizational level [7]. Many of these research questions require an empirical research agenda and a more profound treatment than many of the early empirical studies before 2018 that report which type of organization is using process mining for which application scenario [37].

Since 2020, a second wave of empirical works has gathered insights into how process mining contributes to organizational performance. Contributions such as [21] differ from the earlier application scenario studies in their ambition of developing a theoretical understanding of the causal chain and corresponding mechanisms from process mining adoption to usage and eventually to improved organizational performance. Much of these works use explorative, qualitative, or inductive research methods with the ambition of contributing to theory building. A diverse collection of observations and theoretical arguments on the usage and impact of process mining tools has emerged from these contributions. At the same time, this research body also exhibits weaknesses in terms of theoretical cohesion and theoretical integration of more general streams of information systems research.

This paper makes an effort to integrate into a more holistic theory that can eventually provide a foundation for more deductive and quantitative empirical research on process mining. To this end, we build on the theory of effective use and focus on the individual effect on decision makers [38]. More specifically, we use this theory to organize empirical observations on process mining. Our work contributes to the consolidation of empirical research on process mining and its integration into more general information systems theories. We also identify blind spots in the theory of effective use where empirical insights on process mining provide complementary perspectives.

The rest of the paper is structured as follows. Section 2 summarizes recent empirical work on process mining. Section 3 describes the theory of effective use and builds on it to integrate empirical process mining findings. Section 4 discusses our findings before Section 5 concludes with a summary and an outlook onto future work.

2 Background

This section describes the background of empirical research on process mining. Research on process mining has traditionally focused on developing new and improved algorithms for automatic process discovery, conformance checking, and process enhancement [1]. A first wave of empirical research investigates application scenarios of these algorithms and corresponding tools [37, 39]. The focus of this second wave of empirical research is on the development of theoretical insights into the mechanisms of how process mining provides benefits. To this end, we discuss research that focuses on the work of the analysts and their interaction with process mining tools. Then, we describe contributions that look at the impact on organizational performance.

2.1 Analysts and their Interaction with Process Mining Tools

Research on the impact of process mining tools on the *work of the process analyst* in various domains has been limited to exploratory studies. Early work by Ailenei et al. [2] describes 19 use cases, in essence, analysis tasks that analysts can investigate using process mining tools. They find that identifying the structure of the process, its most frequent path, the distribution of cases over paths, and the compliance with a predefined process models are the most relevant use cases. Interviews by Zimmermann et al. have revealed that analysts perceive challenges in conducting process mining projects [43]. From these interviews, 23 challenges of using process mining are described. What makes the analysts' work difficult appears to be essentially the access to additional information (C14), data access (C6), data extraction (C4), as much as tool knowledge (C11) and analysis focus (C17) [44]. In order to cope with these challenges, analysts apply different types of strategies to understand, plan, analyze, and evaluate their results [42]. Sorokina et al. show that effective strategies of creating process mining results lead to superior performance [35]. Much of these strategies can be related to analyst strategies described in the field of visual analytics [13] and its basic mantra of *overview first, zoom and filter, then details-on-demand* [34]. In turn, the effective use of an analytical tool then becomes an issue of how well these cognitive strategies of the analyst are readily supported by corresponding tool features.

2.2 Organisational Impact of Process Mining Adoption

Research on the impact of process mining on organizational performance has developed in recent years, mostly building on case studies and qualitative research designs. Grisold et al. conduct interviews with process managers who report difficulties in quantifying the value of process mining and issues with an increased level of transparency [21]. Eggers et al. also find a social impact of increased process transparency through process mining, but highlight its benefits for process awareness [15]. This process awareness appears to be the foundation for evidence-based decision-making and overall contributions to organizational value creation, as Badakhshan et al. emphasize [4]. However, not all process mining initiatives progress in this direction. Stein Dani et al. report issues connected with lack of expertise, lack of incentives, loss of interest, or sheer denial [36]. Mamudu et al. identify ten success factors for process mining including stakeholder support, information availability, technical expertise, team configuration, structured approach, data quality, tool capabilities, project and change management, and training [28]. Joas et al. find challenges for organizational impact of process mining with a focus on sustainability reporting in the six categories of the BPM success factors model [23]. Brock et al. develop a process mining maturity model including 23 factors grouped into the five categories organization, data foundation, people's knowledge, scope of process mining, and governance [6]. The list of these factors is extensive, yet there are no quantitative insights into the relative importance of the factors.

2.3 Theorizing the Impact of Process Mining

Some papers point to opportunities for further advancing this research area by building on theories from information systems research [7] and from cognitive research on diagrams [30]. So far, theorizing is limited to the observation that models of technology acceptance [40] and task-technology fit [19] are presumably applicable [7]. There is support from research on business intelligence systems that highlight the applicability of information systems theories including the DeLone & McLean success model, technology acceptance model, diffusion of innovation theory, and the unified theory of acceptance and use of technology [3]. Also personal factors as anxiety, absorptive capacity, self-efficacy and user involvements are discussed, as much as challenges including system acceptance, motivation, fear of losing power, or lack of knowledge [3]. The relevance of cognitive factors has been emphasized in works that build on diagram understanding [30]. In essence, this stream of research stressed the importance of understanding characteristics of analyst tasks relative to the representations that are offered to support the task at hand [27].

These theories however focus on preconditions of use, while offering little regarding how tool-supported task performance feeds back to the behaviour of the analyst. Foregrounding the dynamics of actual usage is the basis for understanding the impact that process mining tools have on the work of process analysts and their decision-making. The theory of effective use (TEU) [38] has been recently adapted for business intelligence systems, a group of systems related to process mining tools. This adaptation provides opportunities to map and integrate the different empirical studies on process mining. In the following, we will pursue this opportunity.

3 Theoretical Integration based on Theory of Effective Use

The theory of effective use has developed from a longer debate about the relevance and characteristics of information systems use. The DeLone & McLean model of information system success had already identified the use construct as of central importance in the causal chain from information system to eventual success. However, use turned out to be difficult to specify from a theoretical angle [31]. Burton-Jones and Grange observed that use is much less of relevance than effective use. They developed their theory of effective use based on key concepts of representation theory, originally defined by Wand and Weber based on Bunge's work on ontology [33]. The original version describes effective use as a chain from transparent interaction with a system towards representational fidelity towards informed action, which all contribute to performance in terms of efficiency and effectiveness [8]. Next, we describe a recent contextualization of the theory of effective use and then use it to integrate diverse findings from qualitative studies on process mining.

3.1 Theory of Effective Use

Recently, the theory of effective use has been extended with resource-related constructs and contextualized for business intelligence (BI) systems [38]. The corresponding model describes three categories of factors with three constructs each that have a hypothetical effect on decision-making efficiency and effectiveness. We discuss these three categories in turn.

Effective Use of BI System: Constructs in this category stem from the original theory formulation of Burton-Jones and Grange, which in essence defines a causal chain from transparent interaction to representational fidelity and informed action [8]. In this context, **transparent interaction (TI)** is defined as "the extent to which a user is accessing the system's representations unimpeded by its surface and physical structures" [38]. Items of this construct relate to the system being easy to use and user-friendly, such that users do not have difficulties interacting with it. **Representational fidelity (RF)** refers to the interaction with the system and "the extent to which a user is obtaining representations that faithfully reflect the domain that the systems represent" [38]. This means in essence that the system's representations correctly represent reality. Finally, **informed decisions (IF)** as a specific type of informed action captures “the extent to which a user acts on the information/output that he or she obtains from the system to improve his or her work performance” [38].

BI Resources: The recent TEU model of Trieu et al. adds three resources to the theory at each of its three stages [38]. A hypothetical factor of transparent interaction is **BI system quality (SQ)**. This is “a measure of the performance of the BI system from a technical and design perspective” [12, 18]. Representational fidelity is expected to be affected by **data integration (DI)**. “Data integration ensures that data have the same meaning and use across time and across users, making the data in different systems or databases consistent or logically compatible [20]. Finally, informed action is affected by an **evidence-based management culture (EBM)**. “An evidence-based management culture involves the use of data and analysis to support decision-making [32].

Learning Activities: The original TEU also assumes the relevance of learning activities [8]. **Learning the system (LS)** is described as a factor of transparent interaction and refers to “any action a user takes to learn the system (its representations, or its surface or physical structure)”. **Learning fidelity (LF)** is described as a moderator of the effect of transparent interaction on representational fidelity. It covers “any action a user takes to learn the extent to which the output from the system faithfully represents the relevant real-world domain”. The effect of representational fidelity on informed action is assumed to be moderated by **learning how to leverage output (LL)**. It refers to “any action a user takes to learn how to leverage the output obtained from the system in his/her work”. Mind though that none of these learning variables were significant in the evaluation of Trieu et al. [38].

The theory of effective use and its application to business intelligence systems points to its relevance for investigating the impact of process mining systems. So far, research on process mining and on effective use have been disconnected.

3.2 Integration of Empirical Process Mining Studies

Recent empirical studies on process mining follow qualitative methods. They contribute observations on process mining use, but with little theoretical integration. The theory of effective use and its application to BI systems offers the opportunity to structure various empirical contributions on process mining. To this end, we focus on the following empirical process mining papers (*the studies* in the following):

1. Badakhshan, Wurm, Grisold, Geyer-Klingeberg, Mendling, vom Brocke: Creating business value with process mining (JSIS 2022) [4].
2. Brock, Brennig, Löhr, Bartelheimer, von Enzberg, Dumitrescu: Improving Process Mining Maturity–From Intentions to Actions (BISE 2024) [6].
3. Eggers, Hein, Böhm, Krcmar: No longer out of sight, no longer out of mind? How organizations engage with process mining-induced transparency to achieve increased process awareness (BISE 2021) [15].
4. Eggert, Dyong: Applying process mining in small and medium sized it enterprises: challenges and guidelines (BPM 2022) [16].

5. Grisold, Mendling, Otto, vom Brocke: Adoption, use and management of process mining in practice (BPMJ 2021) [21].
6. Joas, Gierlich-Joas, Bahr, Bauer: Towards Leveraging Process Mining for Sustainability – An Analysis of Challenges and Potential Solutions (BPM Forum 2024) [23].
7. Kipping, Djurica, Franzoi, Grisold, Marcus, Schmid, vom Brocke, Mendling, Röglinger: How to leverage process mining in organizations-towards process mining capabilities (BPM 2022) [25]
8. Mamudu, Bandara, Wynn, Leemans: Process Mining Success Factors and Their Interrelationships (BISE 2024) [28].
9. Sorokina, Soffer, Hadar, Leron, Zerbato, Weber: PEM4PPM: A Cognitive Perspective on the Process of Process Mining (BPM 2023) [35].
10. Stein Dani, Leopold, van der Werf, Beerepoot, Reijers: From Loss of Interest to Denial: A Study on the Terminators of Process Mining Initiatives (CAISE 2024) [36].
11. Martin, Fischer, Kerpedzhiev, Goel, Leemans, Röglinger, van der Aalst, Dumas, La Rosa, Wynn: Opportunities and challenges for process mining in organizations: results of a Delphi study (BISE 2021) [29].
12. Zimmermann, Zerbato, Weber: What makes life for process mining analysts difficult? A reflection of challenges (SoSyM 2023) [44].

We reviewed the constructs being discussed in these papers and mapped them, where possible, to constructs of the theory of effective use. We will again use the three categories of the recent version of TEU to organize this discussion.

Effective Use and Process Mining: The **transparent interaction** of a process manager with a process mining system (PMS) is mentioned as a challenge by Zimmermann et al. [44]. Kipping et al. report that a potential discrepancy between model and reality is an issue [25]. This relates to what Zimmermann et al. describe as a challenge of process mining suitability [44]. Several observations of the studies focus on the relationship between **representational fidelity** and **informed action**. First, here are observations on how this connection materializes. Both Mamudu et al. and Brock et al. emphasize the need to follow a structured approach or a systematic method [6, 28]. Grisold et al. mention process selection in particular [21]. However, their arguments partially mix a) getting the PMS ready to use (planning, data extraction, project-focused) and b) actual use (analysis and evaluation). Second, Zimmermann et al. describe challenges of drawing conclusions and formulating recommendations [44]. Badakhshan et al. highlight that data-driven decision-making has to be considered separately from the actual implementation of interventions [4]. Both Mamudu et al. and Brock et al. agree that implementation requires attention to change management [6, 28]. Insights do not always yield action, as Stein Dani et al. observe: stakeholders might deny the correctness of analytic insights, may have a lack of incentives to take action, or lose interest for other reasons [36]. Also Eggert and Dyong report doubts about analysis results [16]. Grisold et al. point to potential issues of coping with increased transparency along with a fear of surveillance [21]. These observations relate to what TEU describes as disturbances, i.e. external constraints affecting effective use, but without detailing them in the theory.

BI Resources and Process Mining: According to TEU, **system quality** plays an important role as a factor of transparent interaction. The studies support this view, pointing to the relevance of tool capabilities [28] such as process visualization and process analytics [4]. All studies strongly emphasize the relevance of **data integration**, not only in terms of "the same meaning and use across time and across users", but also in terms of data quality and sheer data accessibility [6, 16, 21, 23, 28, 44]. Often, laborious data preparation [36] is needed to achieve data connectivity [4]. Also evidence-based management culture is mentioned. Brock et al. [6] refer to Kerpedzhiev et al. [24] who point to cultural factors including process centricity, evidence centricity, and change centricity. Martin et al. list a total of ten culture-related challenges including aversion to transparency and resistence to change [29]. Overall, the studies are consistent with TEU, partially providing a more detailed perspective on data issues and tool capabilities.

Learning Activities and Process Mining: The learning variables define the third category of factors. Though they were significant in the evaluation of Trieu et al., there was further support for their relevance in reflection interviews [38]. The studies also support their importance, a.o. by pointing to insufficient skills [23,29,44], the need to conduct training [28], and inappropriate analysis strategies [35]. **Learning the system** relates to observations about technical expertise as a prerequisite [28] and lack of expertise as a roadblock [36]. Regarding **learning fidelity**, Badakhshan et al. describe the need to perceive end-to-end process visualization and performance indicators [4]. For **learning how to leverage output**, Grisold et al. observe issues with understanding how variables inform decision-making [21]. Badakhshan et al. highlight the need to engage in sense-making of process-related information before decisions can be made [4]. Here, Zimmermann et al. identify analysis expertise as a challenges [44]. Brock et al. stress people's knowledge as a factor and point to various aspects of knowledge. They distinguish knowledge of process mining tools, technical basics, data preparation, classical data mining, process mining basics, and advanced applications [6]. Eggers et al. identify shared process awareness as a central construct [15]. In essence, they argue that process mining usage contributes to process awareness, which in turn contributes to process performance. Altogether, the studies confirm the importance of this category, but rather as a matter of skill and expertise (variables of status) instead of learning (variables of action). The study by Trieu et al. [38] partially addresses this concern by using "experience using BI" and "experience working in organization" as control variables.

Other Factors: The studies mention a number of organizational factors that are relevant for the effective use of process mining. Some of them relate to a link with **strategic objectives**. Brock et al. point to the purpose of using process mining [6] and Stein Dani et al. to incentives [36]. Potential internal resistence can be an issue [25], therefore, Mamudu et al. call for stakeholder involvement [28]. Grisold et al. and Martin et al. observe issues with justifying the business case of using process mining [21, 29]. A second category relates to **governance** mentioned in [4, 6, 15]. Brock et al. provide the most detailed discussion. They distinguish general roles and responsibilities plus a governance of methods and tools, processes, and data [6]. Brock et al. also advocate establishing a center of excellence for process mining.

In summary, empirical studies on process mining are largely consistent with propositions of the theory of effective use. The studies provide some more detailed and nuanced perspectives on skills, culture, strategy, and governance.

4 Towards a Theory of Effective Use of Process Mining Systems

Our analysis has defined a theoretical bridge between empirical studies on process mining and the theory of effective use. While the causal path from transparent interaction to representational fidelity to informed action and eventually efficiency and effectiveness is by large consistently reflected in the studies, it is interesting to note that the studies point to those four success factors of BPM beyond the foundational method and technology category, namely strategic alignment, governance, people, and culture [14, Ch.12], also observed by Martin et al. [29]. There is potential to refine and revise the theory of effective use in each of these categories towards a theory of effective use of process mining systems. Here, we focus on relevant, but non-significant constructs of learning and the notion of process awareness.

First, a direction for further developing TEU is to move **from learning to expertise**. The non-significance together with the relevance of learning-related constructs in the study by Trieu et al. [38] points to the need for a revise the theory of effective use. We suggest refocusing on expertise instead of learning. First, the concept of learning has conceptual disadvantages. The TEU constructs refer to actions taken to acquire knowledge. This ignores the status of knowledge, and mixes in diligence and motivation. Second, information systems research has demonstrated the importance of expertise in various studies, highlighting challenges of a revision of TEU. Already in the 1980s, Vitalari identifies a catalogue of eight larger knowledge categories of a system analyst with partially up to 30 different knowledge items [41]. In relation to process mining usage, Brock et al. point to the fact that several categories of knowledge are relevant [6]. Another challenge are the dependencies between the knowledge categories. Mackay et al. find that a lack of technical usage expertise appears to be a roadblock to leveraging domain expertise [26]. Hahn and Lee discuss complications stemming from the division of labour and expertise between business and information technology units in many companies. Cross-domain knowledge turns out to be specifically important for effective collaboration.

Second, a direction for further developing TEU is to move **from semantics to pragmatics**. Zimmermann et al. mentions process domain understanding as an important factor beyond what is visible through the process mining system [44]. Trieu et al. reflect on their study and state that information provided by a system “could still be useful even when representational fidelity was low” [38]. Apparently, even when data quality is often low, managers can still draw conclusions using their business knowledge to make informed decisions. This is in line with the argument of Bera et al. that highlight the strength of pragmatics [5]. Taking pragmatics seriously requires a deeper reflection of the connection between knowledge and tasks at the individual and organizational level [27]. Indeed, Eggers et al. identify different types of use scenarios for process mining, namely explorative analysis versus monitoring, with likely implications for usage [15]. The authors also identify process awareness as a central construct on the path to organizational performance. Mind that this is not necessarily fidelity of the representations in the process mining system, but the shared understanding of the process by the process manager and involved stakeholders. Important to note is also the fact that process awareness goes beyond the ontological description of the process, but rather relates to notions of situation awareness [17] as often discussed in human factor studies. We must also acknowledge the fact that much of the work with process mining systems is rather problem solving than decision making. Both involve uncertainty, but problems are much more open. Campbell characterizes decision tasks by a number of conflicting outcomes (e.g. selecting a new employee), while problem tasks suffer from various paths to arrive at a desired outcome [9]. Chandra Kruse et al. describe various behaviours of how analysts approach such a task: understand the problem and scope, retrieve prior knowledge, look for alternatives, generate new concepts, propose solutions, and finally implement and communicate [10]. Clearly, not all of these behaviours are directly supported by systems, but much of the iterative behaviour is consistently reported in visual analytics research [13] and empirical process mining research [22, 44].

In summary, the non-significance in the study of Trieu et al. [38] and the observations of empirical process mining studies highlight the potential of revising and refining the theory of effective use for process mining systems.

5 Conclusion

In this paper, we have discussed empirical research on process mining. We identified the recent contextualization of the theory of effective use for business intelligence systems as an opportunity to organize and integrate various empirical observations on process mining from twelve recent papers. Overall, we found the studies and the theory consistent in large parts, but there are also opportunities for revision and refinement. We discussed specific opportunities for moving from constructs on learning to expertise and integrating a pragmatic perspective that complements the semantic emphasis of representational fidelity. In future research, we aim to further develop our discussion into a theoretical model and make it subject to an empirical research agenda.

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