Towards the Design of a Process Mining-Enabled Decision Support System for Business Process Transformation

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Abstract. Current approaches to business process transformation rely on normative "de jure" process models which are derived manually, costly to create, error-prone, idealistic, and often deviating from process reality. Theoretically grounded in organizational contingency theory, decision support systems (DSSs) and business process management literature, this design science project proposes the development of a DSS which incorporates bottom-up process mining in addition to other top-down sources of process knowledge for business process transformation. The DSS is intended to provide support in both the selection of an appropriate target process design as well as transformation support on the task level. This design project is conducted within a large-scale digital transformation project of a leading German manufacturing corporation to redesign business processes including the migration of the current SAP R/3 system to the SAP S/4 HANA business suite. Therefore, this design science research (DSR) utilizes a real-life event log comprising transaction data from multiple ERP systems as data source for the process mining module of the DSS and the later evaluation of the artifact. This proposal motivates both the practical and theoretical need for process mining-enabled decision support in business process transformation. Further, this proposal highlights research gaps, outline the DSR approach, and introduces the meta-requirements and the technical conceptualization of the DSS.

Keywords: business process management, process mining, decision support system, design science, process transformation, contingency theory

1 Motivation

Organizational success in the 21st century vitally depends on the ability to navigate in increasingly dynamic environments by constantly adapting the organizational design. Organizations perform business process transformation to restore the fit between the environment and the organizational design to remain competitive (e.g., [1–3]). Numerous environmental shifts and technological innovations fundamentally change organizational boundary conditions (e.g., [4–6]), and thus require organizations to

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transform business processes in response to these internal and external changes. For instance, digital transformation imposes an "inescapable" discontinuity (e.g., [7]), and organizations engage in digital transformation with the replacement of physical processes by information-based processes [8] to enrich purely physical products with value-creating services in response to the emergence of technological innovations as well as changed market economies (e.g., [2]).

However, the transformation of business processes from a current process design X to a new target process design X' requires a comprehensive understanding of the real-world execution of current processes [9] in order to make solid transformation decisions. Furthermore, a clear decision support on how to reach the target design X' is required. Nevertheless, organizations frequently do not to meet these prerequisites for business process transformation. Many organizations possess only limited process insights and a narrow understanding of process execution paths [10–12]. In particular, the understanding of processes in transformation endeavors often relies on feeble "de jure" [13] process models. These "de jure" models are normative and prescriptive in nature, and purely describe how processes were originally intended to be executed during design-time. "De jure" documentations usually merely contain ideal process executions, while most process variants and deviations from ideal to-be specifications are ignored [14]. Therefore, van der Aalst [13] finds the currently prevailing approaches to process modeling to be "disconnected" from process realities. Furthermore, and in addition to weaknesses concerning content and completeness, "de jure" models are derived manually and top-down in a time-consuming and error-prone documentation procedure by process stakeholders, which introduces another dimension of insufficiency in terms of costs. In sum, "de jure" process models provide an unsuitable foundation for decision-making in process transformation.

2 Proposal and Research Question

The design science approach in this project tries to provide a solution to these limitations to organizational transformation capabilities. A possible way to overcome the various insufficiencies of "de jure" process models is to exploit the increasing availability of process data from numerous sources internal and external to organizations [5]. These different data pools which store process information such as information systems (IS) might be utilized to enrich the traditional top-down "de jure" models with bottom-up "de facto" process information in decision-making. The core idea of this research is therefore to explore how "de jure" top-down process information might be enriched by data-driven, bottom-up and "de facto" process information for decision-making in business process transformation.

To operationalize this idea, process mining [15–17] provides a technology, which aims at the automatic discovery of processes from event logs stored in organizational IS [17]. Therefore, process mining yields descriptive and positive "de facto" process analyses which precisely and thoroughly capture process realities [14].

Thus, the aim of this design science research (DSR) project is to provide organizations with a process mining-enabled decision support system for business process transformation. The overarching research question of this DSR project becomes:

Research Question: How to design a process mining-enabled decision support system to support organizations in transformation of business processes?

Process mining has reached a state of maturity by providing widespread tools and techniques to model, monitor, and improve organizational processes, and delivers mature techniques and algorithms to turn data into process knowledge [4]. Current research on process mining has been rather abundant in exploring techniques and algorithms to process event logs (e.g., [18, 19]), in developing software applications and tools (e.g., [9, 16]), in identifying challenges when turning data into process information (e.g., [20]), and in creating visual process representations (e.g., [16, 21]). However, these contributions focus on the "pre-processing" and the mining phase of process mining, while the "interpretation phase" [22] or post-mining phase received significantly less scholastic attention. Thus, further research is needed on the "post-mining phase" to provide an answer to the question of how organizations can actually employ process mining results in business process transformation.

3 Research Methodology

The proposed DSS will be developed in a design science approach. The seminal works by Hevner [23] and Kuechler and Vaishnavi [24] suggest to perform DSR projects in cycles in "build-and-evaluate loops" [23] to iteratively arrive at an optimized artifact instantiation. Thus, this research will conduct two sequential design cycles.

The first initial design cycle comprises a phase to create problem awareness, the formulation of a suggested problem solution, the development of a first DSS prototype, as well as an evaluation phase to discover potential for improvement of the prototype [25]. In the problem awareness phase of the first cycle, an industry alliance was formed. Further, a structured literature review on the search string "process mining" was conducted to validate this proposal as a previously unexplored research gap. In the proposal phase, a further unstructured literature review was conducted to derive preliminary meta-requirements (MRs) for the DSS instantiation. As a next step in the development phase of cycle one, a preliminary DSS prototype will be developed for an order-to-purchase process in the underlying SAP R/3 system. Finally, the evaluation phase will follow the design science evaluation framework as provided by Venable et al. [25] and evaluate the DSS via interviews with process managers and process experts for different processes at different companies of the research site. The prototype will therefore be evaluated in the planning of several real-life transformations of business processes for different companies. The authors in Venable et al. [25] require an evaluation to demonstrate the artifact ability to achieve the intended purpose as well as evidence of problem resolution through the artifact in terms of utility, quality, and efficacy. Furthermore, Venable et al. [25] require developed artifacts to be compared against similar and previously existing solutions. Thus, the evaluation of the

DSS will be conducted to judge the superiority of the DSS to current approaches to business process transformation without the decision support given by the process mining-enabled artifact to evaluate utility and efficacy in business process transformation. In order to quantify these constructs, interviews with an expert group of around 8-10 process managers in the project team and selected individuals from a pool of about 80 specialized process experts across several companies will be conducted to evaluate the helpfulness of the DSS in business process transformation. Besides, the quality of the prototype and the final software artifact will be evaluated according to the properties of "quality" in the ISO25010:2011 standard plus additional quality dimensions from a literature review such as usability, user satisfaction and perceived usefulness.

The second design cycle will further enhance the DSS artifact instantiation by building on the results from the previous design cycle. In addition to a further refinement of problem awareness, the proposal for a solution and the development, cycle two concludes with the finalization of a DSS software artifact and the subsequent summative evaluation [25].

4 Data

An industry cooperation with the IT service company of a large German manufacturing corporation was formed to gain access to several manufacturing companies as research sites to gather qualitative and quantitative data throughout the phases of the DSR project. In 2014, the corporation consisted of several sub-companies operating globally with more than 8.400 employees and about 1bn Euro in turnover.

The industry partner provided an event log of several hundreds of gigabytes of raw data from different SAP R/3 ERP systems for the process mining module of the DSS, plus the additional possibility to conduct qualitative first-hand research such as interviews and quantitative surveys to later evaluate the DSS artifact in a real-life context.

This DSR project is conducted within a large-scale digital transformation project to redesign business processes across sub-companies. The digitalization project further comprises the migration from the status-quo SAP R/3 ERP to the future SAP S/4 HANA architecture. To the best of knowledge, this is the first process mining and decision support research project being able to conduct studies in such a context. As a further research gap in process mining literature, the more advanced process mining techniques have not been tested sufficiently on real-life process data [16] due to a lack of event logs available to researchers. This contribution therefore uses the real-life event log retrieved from the industry partnership, and thus overcomes the weaknesses of many process mining contributions when relying on synthetic, simulated data.

5 Preliminary Results: Meta-Requirements for the DSS

The following section describes the set of meta-requirements which have been identified in the first design cycle. Figure 1 illustrates the conceptualization of the meta-requirements.

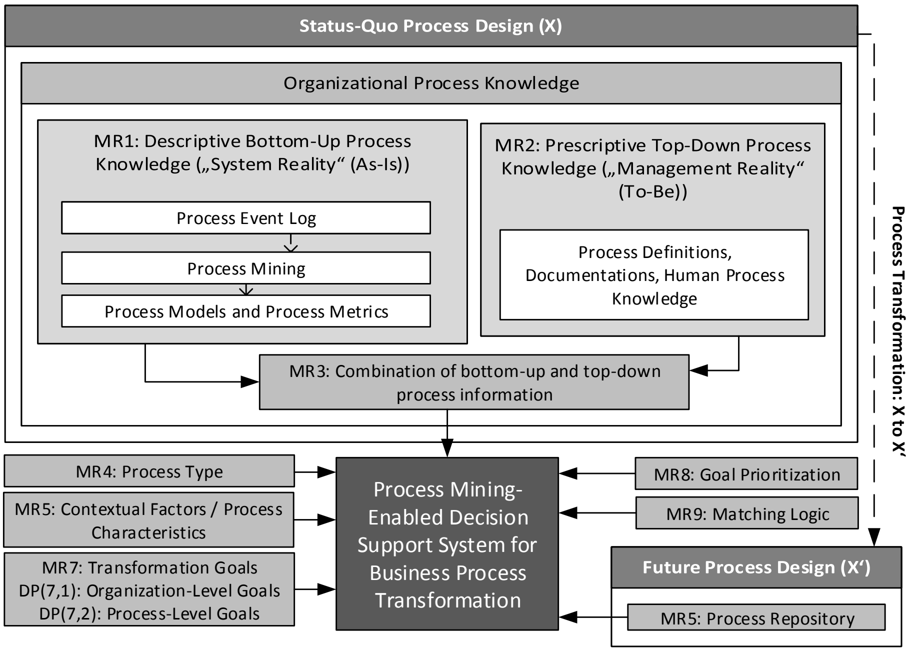

Fig. 1. Meta-Requirements of the Decision Support System

Organizational process knowledge might either be prescriptive (top-down) or descriptive (bottom-up), and might be dispersed across different tangible or intangible "storage locations" in the organization. Therefore, the DSS needs to be able to retrieve process knowledge from different sources, and to combine the different types of process information before deriving transformation decisions.

A potential source of process information is bottom-up process knowledge stored in IS such as ERP systems. These sources include data generated by systems during process execution, such as event log tables within the ERP systems.

MR1: The DSS needs to incorporate descriptive bottom-up process information

These quantitative sources capture process executions "as-is". An exclusive reliance upon process mining in decision-making for business process transformation yields merely an incomplete picture of process realities. Process mining captures only information on process activities within the information system (e.g., [17]), and event logs merely contain a subset of all possible process facets [14, 17]. Insights gained by process mining might be incomplete due to shadow process steps which are not recorded in the system event log. Hence, additional process knowledge needs to be retrieved from top-down sources including qualitative process documentations, definitions, and intangible human process knowledge, leading to MR2:

MR2: The DSS needs to incorporate prescriptive top-down process information

Furthermore, both forms of process knowledge need to complement each other to overcome the mutual insufficiencies. Hence, as bottom-up (descriptive) in MR1 and top-down (prescriptive) process information in MR2 each deliver an incomplete analysis of processes in isolation, both sources need to be combined by the DSS in decision-making to complement each other.

MR3: The DSS needs combine descriptive bottom-up and prescriptive top-down process knowledge

Besides, as this research is embedded in organizational contingency theory [26] by Donaldson [26], which ultimately requires activities of business process management to consider the respective circumstances and contexts of processes, the DSS needs to include the diversity and different types of processes in organizations into decision-making. Therefore, the DSS needs to incorporate process information and to capture information on process type, key process dimensions, and characteristics to provide decision support depending on the respective type of process which is to be transformed.

MR4: The DSS needs to incorporate the type of process into decision-making

Further required by the theoretical embedding into organizational contingency theory [26], process contexts need to be taken into account. The work by vom Brocke et al. [27] requires BPM to be contextual to be effective and defines context as the entirety of factors concerning goals, processes, the organization itself, as well as the environment surrounding the organization.

MR5: The DSS needs to incorporate process context factors and process characteristics into decision-making

In addition to the status quo-oriented meta-requirements, an additional meta-requirement is established concerning the future process state. The DSS needs to possess a repository of potential standard specifications concerning the future target process design from which an optimal process design in X' can be chosen.

MR6: The DSS needs a repository of process designs for the future design in X'

However, to select an "optimum" process design in X' from the repository, needs to be given input concerning transformation goals.

MR7: The DSS needs information concerning transformation goals

Most approaches in BPM usually involve strategic process goals [1, 28] which are compatible with the overall organization strategy [29]. Design principle $DP_{7,1}$consequently demands the DSS to include strategic organizational goals into decision-making. Furthermore, $DP_{7,2}$ imposes another requirement in the form of process-level transformation goal input.

$DP_{7,1}$*: The DSS incorporates strategic organizational-level goals*

$DP_{7,2}$*: The DSS incorporates process-level transformation goals*

A challenge with transformation goals however is their mutual incompatibility as well as different levels of importance allocated to the goals by the DSS users. Decision-making concerning process goals requires multiple criteria decision-making. In turn, this requires the DSS to weigh goals according to importance in advance [30] to give one goal priority over another via an importance ranking (prioritization) among these goals [1].

MR8: The DSS needs an importance ranking among goals to select among target process design alternatives

Finally, the DSS additionally needs to incorporate a matching logic to determine the most suitable target process design X' in the repository. The matching logics needs to compare the status-quo process model X created by the combination (MR3) of bottom-up (MR1) and top-down (MR2) process knowledge with the process models stored in the repository (MR4) and select an appropriate target model X'.

MR9: The DSS needs matching logic to select an appropriate process design X'

Figure 2 provides an overview of the technical conceptualization of the DSS under consideration of the derived meta-requirements in the proposal phase of cycle one.

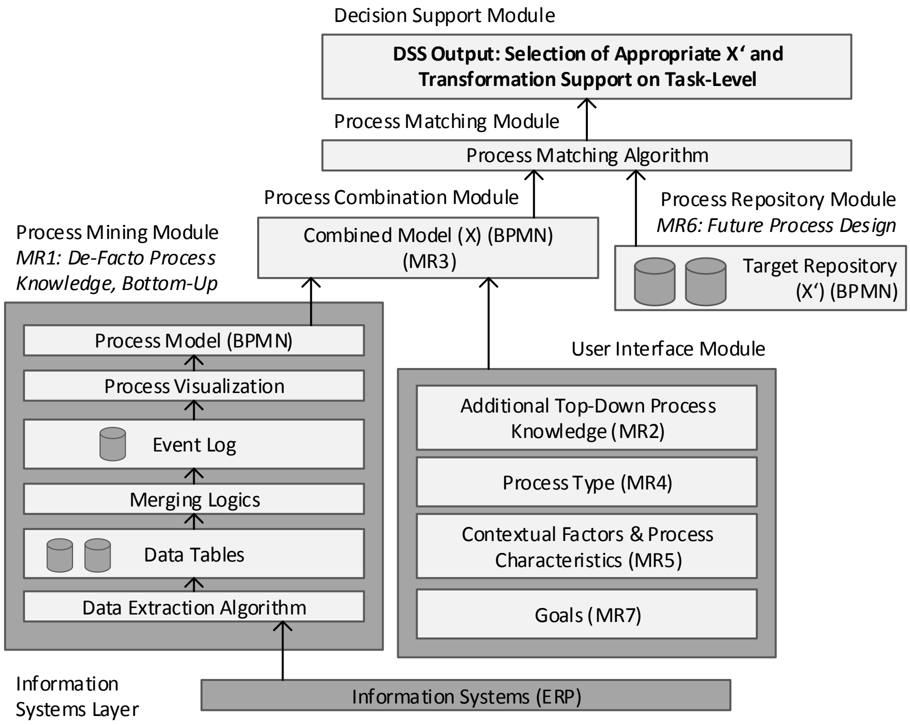

Fig. 2. Technical Conceptualization of the DSS based on Meta-Requirements

6 Conclusion

The ubiquitous need for organizational adaptation in response to changes in the trinity of business, technology, and humans within and around organizations gives a powerful impetus to fundamentally transform organizational business processes. The DSS proposed by this project is created to improve the current way organizations approach business process transformation by providing support in the selection of an appropriate target process model as well as transformation support on the task level. By incorporating "de facto", bottom-up models derived in process mining instead of purely relying on "de jure" documentations in decision-making, the DSS might considerably improve the organizational capability to transform processes. Among the future challenges is the specification of how the task-level transformation support might be implemented.

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