Between Automation and Augmentation: Utilizing Business Process Management to Ensure Operational Support*

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Abstract

Technologies like Process Mining, Robotic Process Automation, and assistance systems shape the way processes are (re)designed and implemented. Together with recent advances in artificial intelligence (AI), the capabilities and opportunities for providing operational support to employees within a company have expanded significantly. The inclusion of AI enables these technologies to incorporate cognitive capabilities and fundamentally changes their scope and interplay. To navigate this broad range of possibilities, methods, instantiations, and related design knowledge are required, especially considering the different approaches to process automation and augmentation. Consequently, these different artifacts must be researched. Therefore, this doctoral research investigates the design knowledge required for process automation and augmentation and examines how organizations can configure these approaches to provide operational support. The paper presents the overall research method, achieved results, and overview, including a road map.

Keywords

Business Process Management, Process Automation, Process Augmentation, Assistance Systems

1. Motivation

Today's working world deals with many challenges, like a lack of skilled workers and an aging workforce [1, 2]. To address this, new technologies are emerging to support companies and employees. Robotic Process Automation (RPA), advanced assistance systems, and generative artificial intelligence (AI) are unique tools that must be used to their strengths. At the core of these technologies lies business process management (BPM), which is responsible for the efficient design, implementation, and execution of business processes [3]. With the goal to provide operational support in business processes, companies face the question of whether to automate, augment, or combine both approaches to support operational work [4, 5, 6]. Answering this question is only possible by achieving synergies between the two approaches regarding employee well-being, task selection, and bridging the gap between instrumental and humanistic outcomes [5]. While nowadays the two approaches seem to answer different questions, historically approaches like workflow automation automated the distribution of documents among process participants and assisted in fulfilling the associated work items [7]. Similar to RPA, workflow automation enacts process activities, while also providing task-related support comparable to an assistance system [7, 8]. Process automation and augmentation are thus not necessarily mutually exclusive alternatives. Depending on the activity and its context, organizations may employ different degrees or combinations of both approaches.

So far, the problems and challenges of these approaches have been identified, but are rarely brought together [5, 6]. A framework for selecting types of process automation distinguishes between traditional process automation, RPA and human work but does not further elaborate on the usage of process augmentation to support humans [9]. Other methods for gathering knowledge for assistance systems exist, but do not address the challenges occurring from knowledge loss through automation [10, 11, 12].

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While both approaches can be applied at the task or process level, establishing synergies between the resulting artifacts remains an ongoing research challenge [5, 6].

To address this issue, the studies outlined in this PhD program aim to answer the research question: **How can organizations configure process automation and augmentation to support operational work under different task, knowledge, technological, and organizational conditions?** In order to properly research this topic, three research objectives (RO) were established:

- RO1: What design knowledge supports the implementation of process automation in operational organizational settings?
- RO2: What design knowledge supports the development and implementation of digital assistance systems for operational employees?
- RO3: Under which conditions should operational activities be automated, augmented, or supported through hybrid configurations?

Design science is chosen as a guiding research paradigm for this research because it enables the design, demonstration, and evaluation of various automation and augmentation artifacts [13]. Following the design science research guidelines of Hevner et al. (2004), viable formalized artifacts arise from a problem statement followed by objectives to enable rigorous evaluation using well-defined methods, with the goal of creating clear and verifiable research contributions [13]. So far, this research has resulted in methods for knowledge acquisition and process automation, as well as success factors and identified threats associated with automation initiatives.

These findings largely support RO1 and RO2 and inform two specific areas, providing structured methods, approaches, and concepts that enable researchers to further develop and conceptualize assistance systems and business process automation. Practitioners benefit from methods and success factors, as well as from the identification of problems that can occur during automation projects. Overall this PhD research aims to investigate how task characteristics, process knowledge, employee expertise, organizational conditions, and technological capabilities influence suitable configurations of operational support.

The remainder of this paper briefly outlines the related work in Section 2. An overview of the overarching research method is given in Section 3. Section 4 highlights and clusters the preliminary results before Section 5 provides a road map on the remaining research tasks in the PhD program and an outlook.

2. Related Work

2.1. Process Mining and Automation

Process Mining (PM) is utilizing event logs to describe as-is processes within BPM [4, 14]. As a minimum requirement, event logs consist of a case identifier, date, and associated activity for the identifier [4]. In the best case, these logs are made available from enterprise resource planning (ERP) systems, workflow management systems, or BPM tools, as these tools provide a sufficient quality of event logs [4]. Missing events thus can lower the quality and dampen the expensiveness and truthfulness of the event log [4, 15], and restoring them can be complicated [15]. When combined with process models and current data, these event logs can support operational support through PM, assisting employees in their everyday work [4]. In general, three methods of PM were initially identified. Process discovery uses the event log to investigate the as-is process and identify findings and deviations [4]. Conformance checking uses existing process models and compares them with the as-is process to identify deviations and generate an improved model [4]. Process enhancements utilize process models and the as-is process to create an improved version [4].

A technology that perfectly matches with PM is RPA, a subset of process automation [16]. Insights generated from PM can be directly translated into actions for RPA [16]. To determine when to use RPA, a framework distinguishes between the number of process instances and their variance [9]. Few variants with lots of instances are prime candidates for traditional process automation [9]. On the other hand, many variants with few instances are too complex to automate and should thus be solved by humans [9]. Between the two, RPA is a promising solution due to its core characteristics [9, 17]. RPA is a lightweight IT intervention that sits on top of existing systems [18]. Set instructions bundled together in a choreography execute tasks across different systems, similar to a human [18, 19].

2.2. Process Augmentation

In contrast to the automated replacement of activities, process augmentation aims to enhance human capabilities by integrating them with advanced technologies such as AI and augmented reality to provide intelligent support [20, 21]. Rather than moving to digital robots for process execution, process augmentation aims for a human-centric design, aware of the given context, in the best case available in real time [22, 20, 23]. While the goal of improved efficiency and accuracy stays the same [24], pitfalls of automation like knowledge loss and ethical aspects like employee replacement are less extensive [12, 25].

A key technology in this context is the use of assistance systems. In the past, most prominently driving assistance systems were the focus of research, but due to AI, recently a shift towards user assistance systems across almost all areas of life can be observed [26]. Nowadays, assistance systems support production, maintenance, and personalized assistance, aiming to support users in their work [24, 27, 28]. Given the degree of intelligence and interaction, basic and advanced user assistance systems can be defined [26]. Basic assistance systems possess a low degree of intelligence and interaction with the users [26]. Advanced assistance systems, in contrast, exhibit a high degree of intelligence, interaction, or both, resulting in intelligent, interactive, or anticipatory assistance systems. [26].

Thus, combining assistance systems with AI seems fitting. Today, AI is understood as a general term for systems that enable machines to perform intellectual tasks [29]. Due to the involvement of communication, coordination, and cooperation with potential peers, AI assistance systems can be used as decision-making tools in AI-based assistance systems [30]. An AI-based assistance system can thus be characterized as a highly versatile support tool and can be seamlessly integrated into the existing work steps or activities [29]. Within these steps, the AI-based assistance system can analyze the environment and project the required data where it is needed [29]. For example, by using AI, the assistance system can support manufacturing workers in quality control and related tasks [31].

Depending on human involvement, process automation and augmentation can complement each other to improve business processes [32]. For example while RPA can lead to knowledge loss and only works within a well-defined context [12, 9], process augmentation works well to externalize, transfer and internalize knowledge [27, 26] whenever RPA is not feasible to be implemented.

3. Research Method

To achieve the overarching design goal, design science is adopted as the guiding research paradigm. Design science is a practice-inspired research approach aiming to develop and evaluate relevant artifacts within a set environment based on rigorous knowledge from foundations and methods [13].

The research objectives RO1 and RO2 both heavily rely on designing artifacts typical of design science. Methods are thus necessary to develop and implement effective techniques for process automation and assistance systems [13]. Models are necessary to conceptualize the core components of potential artifacts [13]. In order to demonstrate the viability of said artifacts, instantiations must be implemented and evaluated [13, 33]. To properly develop these artifacts, depending on the accessibility for company information and longevity of the study, either the design science research methodology by Peffers et al. (2007) or the action design research method by Sein et al. is used [33, 34]. While these methods steer towards the design goal, in order to properly evaluate the artifacts, qualitative methods like interviews and quantitative methods like the usage of performance metrics are used.

RO3 aims to synthesize findings regarding the use of process automation and assistance systems and to identify conditions that influence suitable degrees and configurations of operational support.

A multiple case study is currently planned to compare implemented automation, augmentation, and hybrid configurations. The final operationalization of the study will be refined based on the conceptual framing and scope developed throughout the doctoral research.

By concluding the ROs, the synthesis may also contribute to research on organizational routines by examining how automation and augmentation influence process guidance and execution. Early results indicate the acknowledgment of the value in ostensive process guidance. However, its usefulness rather relies on the worker's level of expertise and performative process output.

4. Preliminary Results

Automation and augmentation stem from the impulse to improve business processes. Both approaches aim to reduce throughput time and error rates while improving the execution quality [35, 28]. Whereas automation aims to reduce and eliminate human involvement from the process [35], augmentation aims to improve the quality of the execution by aiding the human [28]. However, when to use which is not only an economic question but also involves factors centered around the usage of knowledge [11], company culture [35], and available technologies [36].

Currently, the research on RO1 has progressed the furthest. The findings show how task modularization and an appropriate development approach can contribute to successful RPA projects [35]. By understanding the possibilities of the automation platform, a resource-efficient division into modules, the usage of by-products from development, and an early release of automation to free up additional resources, early insights into the inner workings of RPA projects were established [35]. These insights were formalized as a method for implementing RPA following the stages of pre-development, design, development, and operations [37]. In order to expand the usage of RPA using AI, a concept for cognitive automation was developed [36, 38]. To derive quantifiable insights into process automation projects, the logs from an automation initiative at a regional power grid provider were analyzed [39]. The findings reveal that a proper development approach and a sufficiently large user base supports in the development of a project, whereas technical debt and scope or feature creep can yield long-term problems [39].

Building on a long-term research project, RO2 explores the components necessary for an assistance system in the maintenance of power grids. Before any assistance can be given, an identification of the problem or fault must be made [28]. This problem can be diagnosed or predicted using appropriate sensors or algorithms [28]. By combining this problem prediction with ostensive and performative process knowledge, an assistance system can support the employee in solving the problem and, for example, maintaining an asset in the power grid [28]. However, this ostensive and performative process knowledge must be captured according to the domain [*under review*]. Therefore, the IRIS Method was designed and evaluated with the maintenance employees of a power grid provider [11]. By identifying, retrieving, investigating, and structuring domain and process-specific knowledge, it is possible to kickstart the knowledge collection for an advanced assistance system [11]. Four design principles can be derived for the design of an advanced user assistance system, centered on the employee's knowledge level and the degree of assistance required [*under review*]. A conversational extraction during the maintenance process allows to expand the knowledge base and continuously improves the assistance system [*under review*].

These early results show how technology shapes the improvement of business processes. Especially AI now forces researchers and practitioners to rethink the combination of automation and augmentation. Previously process automation relied on BPM and domain specific knowledge [35]. Similarly augmentation and especially assistance systems equally rely on tacit and explicit knowledge to properly function [11]. AI enables the integration of a cognitive component into process automation [36] and enables to create and extend a knowledge base to assist the employees [*under review*]. These recurring dependencies indicate that automation and augmentation can potentially be synthesized through common design dimensions, although the precise conceptualization and boundaries of such a synthesis remain open.

5. Road Map and Outlook

Since RO1 has progressed the furthest, the road map gradually shifts toward completing the work on RO2 and concluding the research by synthesizing the results for RO3. Table 1 highlights the remaining tasks for the PhD program. For RO1, the focus shifts towards understanding the long-term effects of process mining and automation, as well as further applications in ecosystems. The goal is to provide an overview of the application and impact of process mining and automation, expanding beyond a project view in a single company.

Table 1
Road map for the Remainder of the Research

	2026		**2027**	
	Q3	**Q4**	**Q1**	**Q2**
RO1	Long term study on the effects process mining and automation	Process Mining and automation in ecosystems	Conclude RO1	
	Traps for the usage of process mining and automation	Responsible usage of process automation		
RO2	Implementation Method for Assistance Systems	Complete research on the usage of adv. assistance systems	Publish findings on adv. assistance systems	Conclude RO2
RO3	-	Conclude multiple case study on augmentation and automation	Contrast methods and instantiations on augmentation and automation	Provide guidance on the redesign of processes using augmentation and automation

Given the recent emergence of AI-based assistance systems, RO2 aims to derive initial recommendations for their design and implementation. Current work focuses on an implementation method covering planning, knowledge acquisition, conceptualization, and implementation. A three-year action design study further examines the role of ostensive and performative process knowledge and derives design principles for advanced assistance systems.

Beginning in Q4, RO3 will synthesize the findings on automation and augmentation. A multiple case study will identify criteria influencing their use and combination, while a comparison of the developed methods and instantiations will support process redesign and decision-making. This synthesis would particularly benefit from discussions at the Doctoral Consortium regarding three questions: At which level should automation and augmentation be analyzed—tasks, activities, processes, or organizational routines? Should they be understood as a continuum, as combinable design options, or as a multidimensional configuration space? Finally, how can the existing studies be integrated coherently? The intended contribution is integrative design knowledge for configuring automation and augmentation as approaches to operational support.

The PhD project primarily contributes to process redesign and implementation by providing evaluated methods, design principles, and implementation examples. It may also inform research on organizational routines by examining how automation and augmentation influence process execution. For practitioners, the resulting artifacts can serve as guidance and blueprints for operational support. Given the rapid development of AI, the underlying configurations and their implications will require continued investigation.

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Declaration on Generative AI

Generative AI tools like Grammarly and ChatGPT were used for language editing and improving the clarity of selected passages. The author reviewed and takes full responsibility for the final content.

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