Impact of Process Mining Tools on Process Analysis*

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Abstract
Within the field of process mining, there is an emerging topic of research regarding the feedback effects of process mining tools on behavior of process analysts. Due to its more recent emergence, not much research has been done on the topic. To address this gap, my PhD project will focus answering the question how does process automation impact the work of knowledge workers. The setting of auditing is selected for a case study that will examine the short and long term effects of process automation. My PhD research aims to discover both the positive and negative effects stemming from the implementation of process automation within the audit setting. Insights into this topic allow for better organizational decision-making regarding the implementation of process automation tools. Furthermore, it can serve as a basis for further theory building in a developing area of process mining research.

Keywords
Process automation, process mining reliance, automation effects

1. Introduction

It is said that a fool with a tool is still a fool. But what about an expert with a tool? Do they become better experts or lose their expertise altogether? New types of process mining tools are fundamentally changing the way in which knowledge workers are approaching their work. The expectation is that various professional services, such as auditing, will be drastically impacted by those tools' implementation [1] such as process automation. Recent years have seen an increase in uptake of process mining tools by corporations, where they are used to support the analysis of business processes. These tools are especially helpful for knowledge workers who rely on the analysis of processes to do their work.

Research on process mining has traditionally focused on developing or improving algorithms for automatic process discovery, conformance checking, and process enhancement [2]. Recent works on the organizational impact of process mining, highlight the benefits for process awareness [3] and overall value creation [4]. Research on the impact of process mining tools on the work of the process analyst in various domains has been limited to exploratory studies. Interviews have revealed that analysts perceive challenges in conducting process mining projects [5] and apply different types of strategies to understand, plan, analyze, and evaluate their results [6]. At the individual level, theorizing is limited to the observation that models of technology acceptance [7] and task-technology fit [8] are presumably applicable [9]. The focus on these theories is on the preconditions of use, while offering little regarding feedback effects of tool-supported task performance on behavior of the analyst.

The research question addressed in this research project is how does process automation impact the work of knowledge workers. The project will focus on examining how knowledge workers are affected by the implementation of process automation, as well as the benefits and negative feedback effects of process automation on the knowledge worker. The goal is to develop a profound empirical understanding of how process automation affects the work of knowledge workers.

The rest of this paper will be structured as follows. Section 2 first describes related work regarding the specific knowledge work setting of process auditing, second, it describes research regarding human factors and process automation. Section 3 discusses the research objectives. In Section 4, methodologies

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are discussed for each of the associated work packages. Section 5 discusses the preliminary results that have been achieved so far.

2. Related Work

2.1. Research on audit analytics

Auditors play a pivotal role in the efficient working of financial markets by assessing the credibility and quality of corporate financial reports. To this end, they follow a structured judgment and decision-making process. As for most professional knowledge workers, the advancement of technology, including process automation, has created opportunities for auditors to increase the efficiency and effectiveness of their work [10]. The use of data analytics techniques to analyze large volumes of data to identify patterns, anomalies, and potential fraud in an audit setting is commonly referred to as Audit Analytics [11] and has been the subject of multiple research studies [12, 13, 14, 15].

So far, we know surprisingly little about the actual impact of process mining tools on the auditor's analytical work. And indeed, audit research has formulated arguments why the impact of new technology has to be cautiously investigated. Arnold and Sutton (1998) developed the Theory of Technology Dominance for describing the necessary conditions under which professional knowledge workers would rely on intelligent systems, and for theorizing the probability of success or failure as a result of this reliance [16]. The theory crystallized from observations of unintended long-term consequences of the usage of technology by knowledge workers. Such negative consequences are referred to as technology dominance, automation bias, or overreliance on technology [17]. Multiple studies demonstrate the detrimental impact technology dominance can have on decision-making in an auditing context, such as increased biases [18], impeded knowledge development with novices [19], and decreased levels of declarative knowledge held by long-term users of these systems [20].

A more positive note can be found in the scant studies on knowledge transfer from knowledge-based systems to the users of those systems. Preliminary evidence exists that certain design elements, e.g. explanation types or system interfaces embedding expert knowledge structures, have a positive impact on knowledge acquisition by novices [18, 21, 22]. However, research on how the performance of auditors is impacted by tools such as process mining is largely missing.

2.2. Research on human factors and automation

Parasuraman et al. (2000) define automation as putting a system in place that accomplishes a function that was or could be carried out by a human [23]. They emphasize that automation is a gradual phenomenon and distinguish ten levels from no automation at all to autonomous action by the automation without human involvement. Automation can be related to different stages of human information processing along the four stages of acquisition, analysis, decision making, and action.

The availability of automation, can have undesired and unexpected consequences. Next to the desired and expected use, Parasuraman and Riley (1997) describe misuse, disuse, and abuse [24]. Misuse refers to over-reliance, which is likely to result in failures and biases. Disuse describes under-utilization, for instance when floods of false alarms are increasingly ignored. Abuse related to the automation being put in place without considering the complex consequences on human performance. Two negative effects are specifically important in this context: complacency and skill degradation.

Complacency relates to the level of trust a human has developed into automation in a particular setting. High trust, despite the automation not being fully reliable, may lead to over-reliance [25, 26]. In this case, the human pays not enough attention to checking the correct operation of the automation. In this way, complacency represents a short-term effect. Such effects could be relevant in the context of process analysis when analysts develop an over-reliance on the outputs of a process mining tool. Skill degradation refers to a negative effect over a longer period of time. For the context of process analysis, cognitive skill degradation is most relevant. It represents the reduction of thinking, reasoning, and decision- making skills [27].

Both of these concepts have their origin in the field of engineering psychology. In general, however, the humans operating in these settings have the same cognitive characteristics as process analysts, but their tasks are different. Therefore, it is not clear to which extent automation of process analysis may lead to negative side effects and which impact this might have.

3. Research Objectives

As stated earlier, the goal is to develop a profound empirical understanding of the impact of process automation on the work of knowledge workers by answering the research question: how does process automation affect the work of knowledge workers. A collaboration with one of the big four accounting firms is set up to provide an environment in which auditors are given a process automation tool to assist them with their audit tasks. This environment will serve as the basis for a case study that aims to provide the desired empirical understanding mentioned before. The sample size of auditors in the case study is rather limited. As a result, the PhD project will primarily make use of qualitative research techniques. Based on the literature presented in the previous section, the following research objectives are proposed to answer the research question:

- RO1: Determine the influence process automation use has on the work of knowledge workers
- RO2: Develop a list of concrete auditor tasks
- RO3: Determine the core tasks and related skills that constitute expertise in auditing
- RO4: Benchmark the skills of auditors in those core tasks
- RO5: Examine the short and long term effects of process automation on those tasks

4. Methodology

For each of the research objectives proposed in the previous section, a work package is constructed that aims to achieve each objective. The following sections discuss the goals and methodologies used for each work package.

4.1. Work Package 1: Determine the Influence of Process Automation Use on the Work of Knowledge Workers

This work package has two primary goals. The first is to establish an initial model that can be used to measure what kind of effects can be expected when introducing process automation to knowledge work. The second goal is to examine the characteristics of the process automation tool being introduced at the accounting firm. The combination of these two deliverables will serve as a basis for future work packages.

To achieve the first goal, models pertaining to technology acceptance and automation effects from different research fields are collected and compared. These are compared for similarities, contradictions and shortcomings. Determining what drives the use of and reliance on a process automation tool, allows to better determine the scope of the later stages of the project. If the audit case indicates that reliance will be achieved at a slow rate, long term effects may not be identifiable within the scope of this PhD. Knowing the possible effects of process automation will form the basis for further research in later work packages.

The second goal of this work package is to examine the process automation tool being implemented in the accounting firm. The tool has different modules that each serve a different purpose and automate to a different degree. As stated in the related work section, Parasuraman (2000) proposes that automation can occur on ten different levels, and automation can occur to a different degree for each of the stages of human information processing [23]. Using semi-structured interviews and document analysis, a deep understanding is obtained for each for the different modules that the new automation tool offers. For each of the modules, its activities are organized according to the stages of human information processing, and the levels of automation. Once a deep understanding of the tool is realized, this can further help shape what automation effects can be expected when compared to the model from the first goal.

4.2. Work Package 2: Develop a List of Concrete Auditor Tasks

There is currently no comprehensive list present in literature that fully examines all tasks an auditor performs. The goal of this work package is to create this comprehensive list. First, literature will be examined to construct a preliminary list of potential tasks that an auditor performs. This list will then be validated and enriched through document analysis and observations. The partner accounting firm will provide training documents and guidelines that are also given to new auditors. These documents can serve as a first validation for the created list, and provide additional insights more closely related to the case. Observations will then be performed by way of think-aloud protocol. This will capture additional tasks and validate or refute previously collected tasks. This think-aloud protocol will be conducted for auditors of differing levels of expertise. These observations will occur multiple times until a sufficiently comprehensive list of tasks is obtained.

4.3. Work Package 3: Determine the Core Tasks and Related Skills that Constitute Expertise in Auditing

Starting from the comprehensive list of tasks, the goal of this work package is to determine the core of what makes an expert auditor. Research on knowledge work shows that, for auditing, one of the primary measures for expertise is pattern recognition [28, 29]. Those tasks that are central to auditing expertise will most likely heavily involve pattern recognition. To validate this and to identify which of the tasks in the list make up the core of auditing expertise, semi-structured interviews are conducted with audit experts using the ACTA protocol as a guideline [30]. This protocol describes an approach to interviews aimed at capturing and analyzing knowledge regarding applied cognitive tasks.

4.4. Work Package 4: Benchmarking the Skills of Auditors in Core Tasks

To examine the effects of process automation tools, a basis for comparison must be established. The goal of this work package is to benchmark the skills of auditors using an observational study. The goal will be to measure their skills in performing the tasks that were previously established in work package 3. Due to the small sample size of this case, all available auditors will be benchmarked. These auditors vary in level of expertise. This is desirable, as literature states that novice and expert knowledge workers are affected differently by process automation. As a result, a richer spectrum of results can be examined.

4.5. Work Package 5: Examine the Short and Long Term Effects of Process Automation on Core Tasks

Once the process automation tool has been implemented, its effects can be examined over time. The current goal is to determine the beneficial en detrimental impact the process automation had. Expected beneficial effects include decision performance and skill improvement. Negative effects are expected in the form of both complacency in the short term and skill degradation in the long term. Due to the small sample size of auditors in this case, the same auditors that were benchmarked in work package 4 can once again be examined with an observational study for the same skills.

Using the results from this work package, a comparative analysis is made with the model constructed in work package 1. The final result of this work package will be a validated model of the impacts of process automation tools on knowledge workers for the case of auditing.

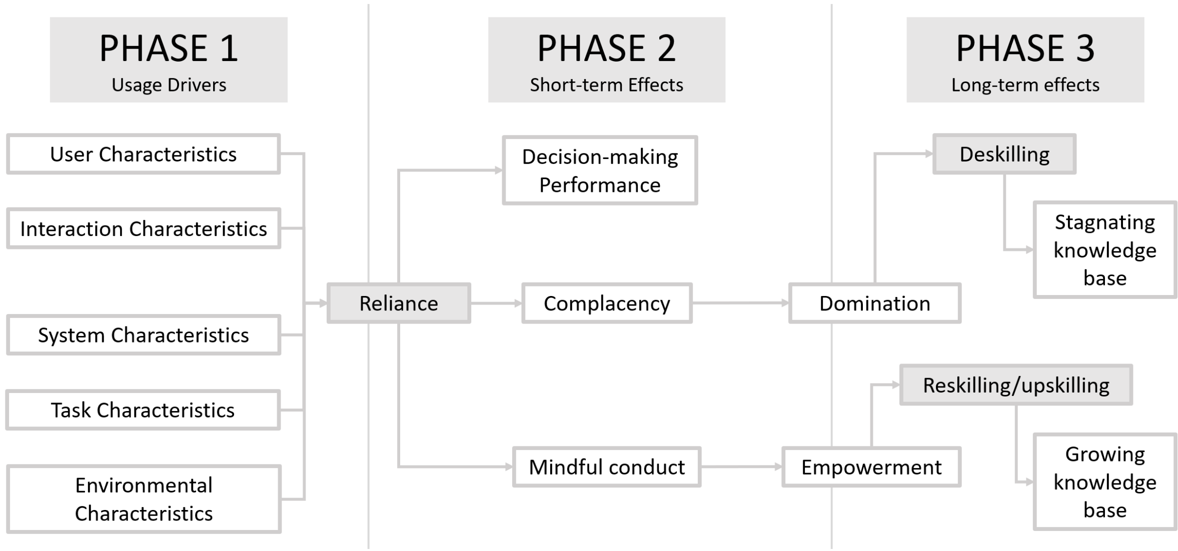

Figure 1: First iteration of model that combines the perspectives on process automation from different fields

5. Preliminary Results

All preliminary results pertain to work package one. For the first goal of work package one, the model shown in Figure 1 is established that combines perspectives from the different research fields of engineering psychology, information systems, and accounting. This model will serve as a basis to determine what drives knowledge workers to use process automation tools. This can be used to determine the speed of adoption of the process automation tool once implemented. Additionally, this model serves to provide insights into the types of effects that can be expected from the implementation of a process automation tool.

The model consists of three phases. The first phase shows different characteristics that drive reliance on a process automation tool. As reliance increases, the second phase of the models describes possible effects that start occurring as a result of effective use and reliance. Short term effects of automation have shown to be beneficial, while effects on skills related to the automated task have shown to be subject to complacency. A relatively underexplored area regarding the topic of process automation effects, is that of indirectly affected skills. These are skills not related to the task being automated. While some research has shown that these skills can improve [31], other research has shown the contrary [32]. Phase three shows the long term effects of process automation on skills. Skills that have suffered from complacency, will start to erode. Skills that have been empowered are theorized to improve over time.

The process automation tool from the accounting firm itself has also been examined on a high level to determine the different levels of automation that are provided to auditors throughout the auditing process.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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