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How the Application of Machine Learning Systems Changes Business Processes: A Multiple Case Study

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HOW THE APPLICATION OF MACHINE LEARNING SYSTEMS CHANGES BUSINESS PROCESSES: A MULTIPLE CASE STUDY

Research in Progress

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Abstract

Machine Learning (ML) systems are applied in organizations to substitute or complement human knowledge work. Although organizations invest heavily in ML, the resulting business benefits often remain unclear. To explain the impact of ML systems, it is necessary to understand how their application changes business processes and affects process performance. In our exploratory multiple case study, we analyze the application of multiple productive ML systems in one organization to (1.) describe how activity composition, allocation, and sequence change in ML-supported processes; (2.) distinguish how the applied ML system type and task characteristics influence process changes; and (3.) explain how process efficiency and quality are affected. As a result, we develop three preliminary change patterns: Lift & Shift, Divide & Conquer, and Expand & Intensify. Our research aims to contribute to the future of work and IS value literature by connecting the emerging knowledge on ML systems to their process-level implications.

Keywords: Machine Learning; Artificial Intelligence; Process Change; Process Performance; Future of Work; Business Value of IT; IS Value; Exploratory Case Study; Multiple Case Study.

1 Introduction

Artificial Intelligence (AI) has made stunning progress over the past decade based on big data, scalable and affordable computing power, and increasingly powerful algorithms (Asatiani et al., 2021). State-of-the-art AI relies on Machine Learning (ML). ML systems can perform sensing, reasoning, and interaction activities without pre-defined solution algorithms. Instead, ML systems learn to predict future outcomes and choose paths of action by extracting patterns from diverse data (Murphy, 2012). Therefore, ML systems can be applied to an increasing range of different work domains and have a particularly pronounced impact on knowledge work, which previously required the expertise and cognitive abilities of human professionals (Faraj et al., 2018).

Organizations strive to exploit ML systems in order to increase their performance. But although ML investments are growing fast (Kappelman et al., 2019), only 20% of ML-based efforts are expected to deliver business benefits (Gartner, 2019). Organizational performance results from the work conducted in sets of coordinated activities referred to as business processes (Weske, 2019). Potential benefits of ML systems can be realized when such systems are integrated into business processes to substitute or complement the knowledge work of human professionals (Melville et al., 2004; Grønsund & Aanestad, 2020). Depending on how and where in an organization ML systems are applied, integration into a business process can take different forms and have specific “ripple effects” (Raisch & Krakowski, 2020, p. 13) on related activities throughout the process. Inter alia, the introduction of an ML system to support one activity in a process can lead to the emergence of new activities, make other activities obsolete, stipulate activity reallocation to different human and technological agents, and trigger changes in the sequence of related activities. Those changes impact process performance in terms of process efficiency and process quality, which in turn contribute to the overall organizational performance (Melville et al., 2004). To explain and predict how and when ML systems can lead to business benefits, it is therefore necessary to understand how ML systems change business processes and the activities comprising them.

Research has recently made notable progress in isolating and explaining some of the idiosyncratic process changes caused by the introduction of ML systems. On the one hand, due to the data-driven approach, ML systems can often make better and more timely predictions than prior, solely knowledge-based technologies such as expert systems and, in some cases, even human experts. However, learning from patterns in data also poses three specific risks that need to be mitigated in organizations to ensure safe and reliable use (Grønsund & Aanestad, 2020): First, ML systems can draw incorrect conclusions in novel and uncommon situations. Second, it can be difficult for humans to understand why and how a system arrives at certain conclusions. Third, ML systems may learn and amplify biased behaviors that human professionals are unaware of. Consequently, prior work highlights the emergence of new activities to continuously monitor and refine ML systems (e.g., Asatiani et al., 2021; Grønsund & Aanestad, 2020). On the other hand, the introduction of ML systems can lead to the reallocation of existing activities between human professionals and the ML system. Prior research has developed different conceptualizations of those activity reallocations, including the automation-augmentation dichotomy (e.g., Raisch & Krakowski, 2020), the spectrum of potential human-machine configurations (Grønsund & Aanestad, 2020), and the delegation of activities from humans to machines and vice versa (Baird & Maruping, 2021). Overall, the aforementioned studies indicate that the introduction of ML systems can lead to the emergence of new activities and to a reallocation of existing activities. In spite of its merits, extant research lacks a detailed consideration of other process changes that can be caused by the introduction of ML systems such as the abandonment, combination, or decomposition of activities and changes in activity sequence. Furthermore, the introduction of ML systems can lead to changes in multiple activities in a process. These changes can be interrelated and can have different, potentially opposing effects on process efficiency and process quality. Still, prior research has not systematically discussed the interdependencies between process changes and has not consistently linked process changes to their performance implications. Consequently, extant knowledge cannot fully explain the specific effects of ML systems on business processes and process performance.

Recent studies have also made first attempts to explain how process changes vary across different application scenarios. On the one hand, prior work provides taxonomies of ML system types and task characteristics that may shape the reallocation of existing activities and the emergence of new activities in business processes (e.g., Baird & Maruping, 2021). On the other hand, recent single case studies have started to explain how the application of specific ML systems changes specific processes (e.g., Asatiani et al., 2021; Strich et al., 2021). Nevertheless, it remains unclear which effects different types of ML systems have across their broad range of applications. Consequently, there is a lack of systematic conceptualization of the influence the ML system type and task characteristics on process changes.

To contribute to a more comprehensive perspective on the effects of ML systems on business processes and process performance, we seek to explain how entire processes change based on the type of ML system and the characteristics of the supported task. We therefore study three research questions:

1. How do business processes change when they are supported by ML systems?
2. How do changes in business processes depend on the ML system type and task characteristics?
3. How do changes in business processes affect process performance?

2 Foundations

2.1 Machine Learning Systems

ML refers to "a set of methods that can automatically detect patterns in data […] to predict future data [or] perform other kinds of decision making under uncertainty" (Murphy, 2012, p. 1). We conceptualize

ML systems as information systems that apply ML to perform sensing, reasoning, or interaction activities (based on Rai et al., 2018). The learning ability distinguishes ML systems from prior technologies. It enables high predictive performance across a broad range of activities, but also limits the transparency and explainability of ML systems, so humans often cannot comprehend the reasoning behind ML outputs or identify incorrect and biased conclusions (Asatiani et al., 2021; Kellogg et al., 2020; Faraj et al., 2018). Furthermore, implementing ML systems requires a constant monitoring and refinement of the underlying algorithms with human expert knowledge (Grønsund & Aanestad, 2020). Consequently, organizations that apply ML systems need to make idiosyncratic adjustments to their processes in order to leverage the benefits of ML systems while mitigating their shortcomings.

Based on their sensing, reasoning, and interaction capabilities, four *ML system types* can be distinguished (Table 1): (1) reactive ML systems that only respond to expected stimuli; (2) supervisory ML systems that monitor developments and identify deviations from a norm; (3) anticipatory ML systems that predict needs of relevant stakeholders; and (4) prescriptive ML systems that collect all necessary information and make business decisions (based on Baird & Maruping, 2021).

ML system type	**Sensing and reasoning capabilities**	**Interaction capabilities**
Reactive	React to relevant expected, immediate, or proximal stimuli	Take actions or alert human agents
Supervisory	Monitor and identify deviations from the norm or the status of goal progression	Take actions or guide human agents to return to the norm or enhance probability of goal progression
Anticipatory	Anticipate needs or wants of relevant stakeholders	Take actions or provide information or recommendations to human agents
Prescriptive	Collect all necessary information and perform behavior-based or outcome-based decision making	Take actions or prescribe actions

Table 1. Types of ML systems (based on Baird & Maruping, 2021).

As ML systems can “emulate the ways in which tacit knowledge is acquired by [professionals]” (Faraj et al., 2018, p. 6), they are expected to have a particularly pronounced impact on knowledge work. ML system can either completely take over activities or significantly change the activities currently performed by human professionals (also called ‘knowledge workers’; Strich et al., 2021; Faraj et al., 2018). Therefore, we focus on how ML systems affect business processes involving knowledge work.

2.2 Business Processes and Process Performance

We define a *business process* as “a set of activities that are performed in coordination in an organizational and technical environment” (Weske 2019, p. 5). The sequence of activities depends on execution constraints such as data dependencies or other preconditions for activities. Jointly, “[t]hese activities […] realize a business goal” (ibid.). The task concept is used ambiguously in connection with business processes: on one hand, it is used as a synonym for ‘activity' (e.g., Dumas et al., 2013). On the other hand, it is used to refer to the outcome or action goal of a business process (e.g., Gaitanides, 2012). Following the latter view, we use ‘activity’ to refer to the execution of specific work by human or technological agents within a business process and ‘task’ to refer to the action goal of a business process.

As business processes integrate activities to realize business goals, we view *process change* in terms of changes in the involved activities. First, the set of activities performed in a business process (= activity composition) can change if new activities emerge or current activities become obsolete, are combined, or are further decomposed. Second, activities can be allocated to different human or technological agents. Third, the sequence of activities can change as ML systems alleviate or impose execution constraints (Weske, 2019). Those process changes impact *process performance*, which comprises process efficiency and process quality and contributes to overall organizational performance (Melville et al., 2004). Process efficiency encompasses the cumulative time and cost required to execute the activities in a business process. Process quality refers to the degree to which a business process accomplishes its goal, including both procedural quality (i.e., correctness) and output quality (i.e., effectiveness; Gaitanides, 2012).

Due to their learning ability, ML systems can perform various activities in business processes that fulfill diverse tasks. Hence, we do not restrict our research to specific *task characteristics* a priori, but seek to identify which task characteristics have an important influence on how business processes change. Thereby, our research also remains analytically open for other explanations based on emerging aspects.

In sum, we study how the interplay between ML system type and task characteristics causes different process changes and impacts process performance. This perspective is consistent with the IT Business Value Model by Melville et al. (2004) and is visualized in our conceptual framework (Figure 1).

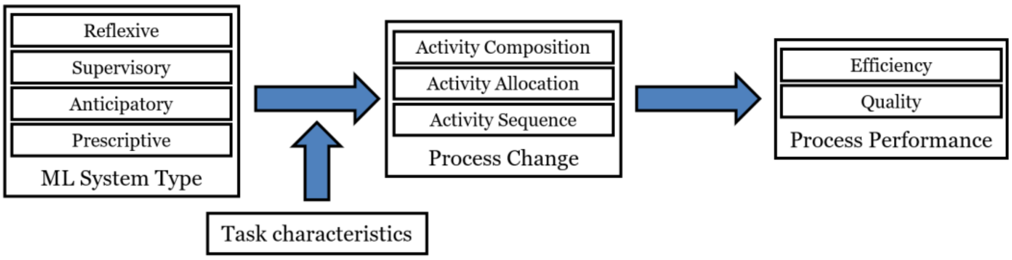

Figure 1. Conceptual Framework (based on Melville et al. 2004).

2.3 Effects of Machine Learning on Business Processes

Although research has not primarily addressed the impact of ML systems on business processes, emergent conceptual considerations and empirical results point towards significant changes in activity composition, allocation, and sequence caused by the introduction of ML systems. Based on our literature review, we synthesize existing knowledge on process changes and identify remaining research gaps to substantiate our research questions (Table 2).

Changes in *activity composition* are mentioned across all research streams. In particular, multiple new activities can emerge within business processes when ML systems are introduced: first, studies describe that ML systems need to be continuously adjusted to ensure their continuous reliability and accuracy. These novel activities go beyond the traditional notion of IS development being separated from the IS use process as they become part of the supported business process (Sturm et al., 2021; Grønsund & Aanestad, 2020). Second, studies report that ML systems require additional evaluation and control activities to mitigate their limited transparency and to ensure both reliable outcomes and human trust (Asatiani et al., 2021; Jussupow et al., 2021; Lindebaum et al., 2020). Third, the presence of ML systems can make it necessary for professionals to perform additional activities to protect or strengthen their professional role identity and prevent over-dependence on the ML system (Strich et al., 2021; Newell & Marabelli, 2015). Fourth, some studies show how ML systems enable professionals to perform new activities that improve process quality (Strich et al., 2021; Faraj et al., 2018).

Likewise, changes in *activity allocation* are identified across all research streams. On one hand, ML systems have been shown to fully or partially take over activities related to coordination or requiring tacit knowledge from humans (Curchod et al., 2020; Faraj et al., 2018). On the other hand, human resources are reallocated to perform many of the emergent new activities described above. Baird & Maruping (2021) introduce the concept of IS delegation to reflect the fact that the agentic behavior of ML systems allows for the reallocation of activities both from humans to machines and vice versa, depending on the characteristics of the supported task and the capabilities of human and technological agents. As ML systems' capabilities are able to surpass humans' capabilities (Faraj et al., 2018), human resources may be freed up to perform activities to improve and control ML systems and to improve process quality (Strich et al., 2021).

Changes in *activity sequence* are discussed less explicitly by prior research. Nevertheless, the chronological order of activities may change for at least two different reasons: First, feedback loops between humans and ML systems may occur (Raisch & Krakowski, 2020; Grønsund & Aanestad, 2021). Second, ML systems may provide specific information, prompt humans to make decisions, or recommend specific actions at different points in the process, thereby alleviating or imposing execution constraints and leading to the earlier or later execution of related activities (Kellogg et al., 2020).

Literature Stream	**Key concepts**	**Selected Sources**	**Effects on Business Processes (activity composition, allocation, and sequence)**
Human-machine configurations	Automation and augmentation	Raisch & Krakowski (2020)	• New activities or changes in activity sequence due to feedback loops • Reallocation of activities between humans and ML systems
	Human-in-the-loop configurations	Grønsund & Aanestad (2020)	
	Delegation to and from agentic IS	Baird & Maruping (2021)	
Accountability (“controlling the algorithm”)	Transparency, explainability, opacity, black-boxed performance	Asatiani et al. (2021), Kellogg et al. (2020), Faraj et al. (2018)	• New activities to alter ML systems (within the business process) • New activities to evaluate and control ML systems • Reallocation of human resources to new activities
	Substantive rationality, initial setup of ML systems, human altering and auditing activities	Sturm et al. (2021), Lindebaum et al. (2020), Grønsund & Aanestad (2020)	
	Sociotechnical envelopment	Asatiani et al. (2021)	
Algorithmic control (“being controlled by the algorithm”)	Algorithmic direction, evaluation, and discipline	Kellogg et al. (2020)	• New activities or changes in activity sequence when ML systems prompt humans to decide or recommend actions • Reallocation of coordination activities from humans to ML systems
	New forms of coordination and control	Curchod et al. (2020), Faraj et al. (2018)	
Professions and expertise	Transformation of expertise in organizations	Faraj et al. (2018)	• New activities to improve process quality (e.g., apply ML outputs, explain ML results) • New activities to protect or strengthen professional role identity • Reallocation of activities requiring tacit knowledge from humans to ML systems • Reallocation of human resources to new activities
	Professional role identity and new algorithmic occupations	Strich et al. (2021), Kellog & Valentine (2020)	
	Dependence on the algorithm	Newell & Marabelli (2015)	
Human cognition and behavior	Trust in the algorithm and cognitive evaluation	Jussupow et al. (2021)	• New activities to evaluate and understand the ML system • New activities to verify ML system output in case of a lack in trust the system • Potential new activities if humans deviate from ML system recommendations
	Algorithm aversion	Burton et al. (2020)	
	Negative worker experiences, resistance, and “algoactivism”	Kellogg et al. (2020), Pachidi et al. (2020)	

Table 2. Literature Review.

In summary, extant research indicates several potential changes in activity composition, allocation, and sequence based on ML systems. However, three important research gaps remain underexplored on the way to understanding how ML systems change business processes: First, it is not clear whether the identified set of potential changes is sufficiently exhaustive and specific to cover the most relevant effects of ML systems. The reviewed literature highlights the emergence of new activities and the reallocation of activities between humans and ML systems, but only scarcely discusses changes in activity sequence or other potential changes in activity composition such as the abandonment, combination, or decomposition of activities. Furthermore, interdependencies between the identified process changes, which could manifest in stereotypical change patterns, have not been systematically discussed. Second, there is no systematic conceptualization of how process changes depend on the ML system type and the characteristics of the supported task. Prior research either discusses the effects of a specific ML system performing activities to fulfill a specific task or it does not specify either. Third, the effects of process change on process performance remain unclear. While the reallocation of activities to ML systems can contribute to process efficiency due to faster cycle times and lower personnel costs, new activities can lead to opposing efficiency losses. Similarly, improvements in process quality do not only depend on the activities performed by ML systems, but need to be realized across the entire business process. Hence, the multiple, potentially conflicting performance effects of ML systems can only be explained based on a comprehensive understanding of how ML systems change business processes.

3 Methodology

The application of ML systems to substitute or complement knowledge work causes novel patterns of change in business processes, but limited theoretical knowledge exists to explain how those process changes depend on the ML system type and the characteristics of the supported task as well as how they impact performance outcomes. We adopt an exploratory research approach through a multiple case study to discover new, contextual knowledge (Yin, 2009; Eisenhardt, 1989). The unit of analysis are business processes supported by ML systems in productive use. We apply operational construct sampling to select cases for all four ML system types (Patton, 2002). We are currently collecting 8-12 cases of ML-supported processes from 2-3 large manufacturing firms to enable literal replication within and theoretical replication across ML system types while ensuring comparability.

We have conducted an applicability check to ensure external validity and refine our research design (Rosemann & Vessey, 2008). It has been based on two focus group discussions with experienced data scientists from the central ML unit of a manufacturing company as well as 12 semi-structured interviews on challenges in realizing value from ML systems with ML practitioners, consultants, and researchers.

Rich qualitative data is being collected to the point of theoretical saturation through semi-structured interviews, field observations, and document analysis. An interview guide has been developed based on our conceptual framework and includes questions regarding the extent of productive system use, supported tasks, and ML system characteristics as well as the business process and process performance before and since the system introduction (Yin, 2009). After initial focus group discussions, a first round of 31 interviews at has been conducted between September 2021 and March 2022 with system users, managers, and system developers at one organization. We captured information on the ex-ante processes before system introduction through archival documents such as development project proposals, training materials, and historical process documentation as well as interviewee reports. Descriptions of the current ML-supported process are compared to field observations of productive ML system use. Process performance is assessed by combining interviewee's qualitative descriptions and quantitative estimations of changes in process efficiency and quality with available quantitative performance indicators provided by the case company.

Data analysis is based on an iterative coding approach including initial, axial, and theoretical coding (Saldaña, 2013). Initial coding includes both descriptive codes derived from our conceptual framework to categorize process changes and performance impacts (incl. activity composition, allocation and sequence as well as process efficiency and quality) and in-vivo codes to explore potential explanations of process change in terms of task characteristics and ML system characteristics. Through axial coding, the initial codes are iteratively refined, aggregated, and interlinked to uncover and explain patterns of process change. We are in the process of combining analysis methods for explanation building, including case narratives, cross-tabulation, and pattern matching techniques (Miles & Huberman, 1994). Subsequently, identified relationships will be reduced to develop parsimonious, generalizable propositions. One potential outcome is a taxonomy of change patterns including explanations of their antecedents and effects on process performance.

4 Preliminary Findings

Our preliminary findings are based on initial data on five ML systems (C1-C5), which are in productive use at one organization. We draw upon interviews, focus group discussions, research memos, and archival documents to substantiate our preliminary findings. Based on a detailed analysis of the cases, we identified three preliminary patterns of process change (Table 3).

First, in the *Lift & Shift* pattern, human agents are relieved of complete activities (the burden is "lifted") as these activities are reallocated ("shifted") to ML systems. Free from their original responsibilities, professionals redirect their attention towards planning, preparation, and control of ML activities. These changes are based on reactive ML systems that only respond to expected stimuli, so the supported tasks need to be structured with pre-defined inputs and outputs. Efficiency increases due to higher throughput at the same human effort. Higher accuracy of the ML systems and the possibility to repeatedly execute activities with varied parameters can improve process quality. For example, in the Product Variant Testing case (C1), the ML system detects patterns in pictures of experiments with product variants and assesses how well the product variants worked under the given circumstances. Human professionals, who previously conducted this assessment manually, instead focus on planning additional experiments with a broader variety of product features and testing conditions. Both efficiency and quality improve due to higher throughput and better research results as the risk of “missing a good variation” is reduced.

<table>
<tr><th rowspan="2">Change Pattern</th><th rowspan="2">Cases[1]</th><th rowspan="2">ML[2]</th><th rowspan="2">Task[3]</th><th rowspan="2">Changes in Business Process</th><th colspan="4">Impact on Process Performance[4]</th></tr>
<tr><th colspan="2">Efficiency</th><th colspan="2">Quality</th></tr>
<tr><td>Lift & Shift</td><td>(C1) Product Variant Testing</td><td>Reactive</td><td>Structured</td><td>• New activity: more extensive planning and preparation of experiments
• Reallocation of variant testing activities to ML system
• More iterations, same activity sequence</td><td>+</td><td>Higher throughput, same amount of human effort</td><td>+</td><td>Higher success ratio, reduced risk to “miss a good variation”</td></tr>
<tr><td>Divide & Conquer</td><td>(C2) Customer Credit Assess-ment</td><td>Prescriptive</td><td>Decomposable</td><td>• Activity decomposition: standard credit assessment of customers reallocated to ML system, humans handle exceptions
• Reallocation of human resources to new activities in exception handling, monitoring, and credit risk reduction (e.g., cust. engagement, renegotiation)</td><td>=</td><td>Less effort per credit, more effort for new activities, stable throughput</td><td>+</td><td>Better exception handling, additional time spent for risk reduction</td></tr>
<tr><td rowspan="3">Expand & Intensify</td><td>(C3) Liquidity Planning</td><td>Reactive</td><td rowspan="3">(no restrictions)</td><td>• Existing planning process retained
• New activity: workshops to evaluate, adjust, and incorporate ML predictions
• Multiple feedback loops</td><td rowspan="3">-</td><td rowspan="3">Additional effort to
• review, evaluate, and adjust ML output
• take further actions (check assets, process offers)</td><td>=</td><td>ML output only used for minor adjustments</td></tr>
<tr><td>(C4) Predictive Mainte-nance</td><td>Supervisory</td><td>• Existing maintenance process retained
• New activities: review alerts, conduct recommended checks on assets
• Reallocation of resources from corrective to preventive maintenance</td><td>+</td><td>Higher share of defects prevented</td></tr>
<tr><td>(C5) Product Recomm-endations</td><td>Anticipatory</td><td>• Existing customer relationship management process retained
• New activities: evaluate product recommendations (“not ridiculous”), calculate suitable prices, make offers</td><td>?</td><td>Information on sales effects not available yet</td></tr>
<tr><td colspan="9">1 Ongoing collection of further cases and in-depth data (interviews, documents, field observations); 2 ML system type
3 Task characteristics; 4 Changes in process efficiency and quality: (+) increase, (=) no change, (-) decrease, (?) unclear</td></tr>
</table>

Table 3. Preliminary Results (based on initial data collection).

Second, in the *Divide & Conquer* pattern, the activities of the original process are divided and their parts are allocated to ML systems or human agents. Thereby, the particular strengths of both ML systems and human professionals can be exploited for jointly completing (“conquering”) the task. This is only possible if the supported task can be further decomposed. Prescriptive ML systems collect the necessary information and evaluate whether human expertise is required. Process efficiency does not change as overall throughput and human effort remain stable. However, process quality can improve as a result of the selective, more targeted application of human expertise to a subset of their original activities. In addition, professionals can reallocate freed-up capacity to new, value adding activities. For instance, the ML system in Customer Credit Assessment (C2) automatically assesses the credit worthiness of customers in standard cases and only prompts humans to make decisions in exceptional cases. Process efficiency is not affected as the same number of assessments is done with the same overall human effort; process quality improves as credit risk is further reduced because human professionals can focus on exception handling and “spend their freed-up time” on additional other risk-reducing activities, such as customer engagement and renegotiation.

Third, in the *Expand & Intensify* pattern, ML systems act as complementary sources of information or advice and the process is expanded with additional activities to review, evaluate, and adjust ML system outputs. Thus, human professionals continue to perform the activities of the original process, but the sequence of activities can change as information becomes available earlier and as professionals interact with ML systems in feedback loops. Overall, the process is intensified because humans need to take additional, earlier, or more frequent actions to incorporate ML system outputs. This approach does not require the supported task to be structured or decomposable. It leads to additional effort across ML system types, so process efficiency generally decreases. Conversely, process quality seems to improve with novelty and future-orientation of ML system outputs, i.e., from reactive through supervisory to anticipatory ML systems. In Liquidity Planning (C3), the ML system predicts cashflows for different legal entities of the organization. In addition to the original process, finance professionals evaluate, adjust, and incorporate the ML predictions through a series of workshops because finance professionals "need to understand the data and [potential] outliers in detail". Consequently, efficiency decreases. As the reactive ML system only considers "historical data and environmental factors" that are also available to the professionals, its recommendations only result in minor adjustments of the liquidity plans with minuscule quality improvement in terms of more precise forecasts. In Predictive Maintenance (C4), the ML system monitors asset parameters during production and alerts maintenance professionals in case of anomalies. Reviewing alerts and checking assets causes significant effort for human professionals, so the ML system needs to "be conservative" with alerts to minimize effort caused by false positive alerts. Nevertheless, the supervisory ML system provides timely notifications to prevent more defects in production assets, so process quality improves as adverse events and unplanned maintenance are prevented. In Product Recommendations (C5), the ML system anticipates potential further needs of business customers and recommends cross-selling opportunities to sales professionals. Sales professionals need to evaluate whether potential offers are suitable given the customer's technical and regulatory restrictions to avoid giving "ridiculous recommendations" that could damage the relationship to their business customers. These additional evaluation activities decrease efficiency. Information about effects on process quality (e.g., sales volume) was not yet available during initial data collection. Nevertheless, stakeholders expect that sales numbers have increased based on the novel information provided by the anticipatory ML system.

Overall, the three preliminary patterns depict how process changes depend on ML system type and task characteristics and how they affect process performance. Sufficiently structured tasks can be supported by reactive ML systems, leading to a Lift & Shift pattern with improved process efficiency and quality. Decomposable tasks can be supported by prescriptive ML systems, resulting in a Divide & Conquer pattern with improved process quality, but without efficiency gains. All types of tasks can be supported by reactive, supervisory, or anticipatory ML systems in an Expand & Intensify pattern where process quality can be improved if ML system outputs are novel and future-oriented while efficiency decreases.

5 Next Steps and Expected Contributions

We continue to collect data on cases at the first organization and have started to collect initial case data at a second firm. We will refine our results to develop parsimonious, organization-independent patterns.

Our research has started to describe, classify, and explain the effects of ML systems on business processes as a basis for further theorizing. We have (1.) identified three preliminary patterns of process change involving diverse changes in activity composition, allocation, and sequence; (2.) related them to their antecedents in terms of task structure and decomposability as well as future-orientation of ML output; and (3.) started to explain their multiple, potentially opposing effects on process efficiency and process quality based on changes in throughput, execution frequency, selective application of human expertise, new value-adding activities, and the future-orientation of ML output.

Thereby, we strive for three contributions. First, we enrich the discourse on organizational effects of ML systems and their impact on the future of work. We develop an exhaustive conceptualization of potential process changes resulting from ML systems. We thereby expand findings from prior literature by including not only activity emergence and reallocation, but also activity decomposition and changes in activity sequence, and by relating process changes to their antecedents and effects on process performance. Second, we aspire to corroborate the typology of agentic IS artifacts by Baird & Maruping (2021) by applying this framework to productive ML systems. Our findings add to understanding how and why ML-based IS artifacts differ in their organizational effects. Third, our framework contextualizes the process-level perspective of the IT Business Value Model by Melville et al. (2004). Our results depict how a specific class of information systems impacts business processes and process performance.

Our research results can serve as practical tools to understand, explain, and potentially predict the effects of ML systems. Detailed case descriptions can help practitioners to grasp the range of potential changes and challenges resulting from ML systems. Our framework and explanations can be applied to diagnose reasons for unexpected performance outcomes, predict potential benefits, and guide investment decisions and implementation choices.

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