

## Transition to Human-AI Work: Shifts in Routines' Dynamics and the Implications for Roles in Knowledge-Intensive Work

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### Abstract

*As solutions based on artificial intelligence grow pervasive in knowledge-work organizations, such cognitive technology is being applied both to automate and to augment work heretofore carried out predominantly by humans. This has profound socio-technical implications for the work practices in that new means of conducting associated routines are changing the knowledge workers' involvement, transforming interaction between the human agents and information systems within the socio-technical system. Taking a processual approach to exploring how such deep transformation extends to the core of the knowledge workers' work roles, an interpretive study examined the role transformation unfolding over two years at a financial-accounting company that was developing and implementing an artificial-intelligence system for its services. This processual study offers empirically grounded contributions in outlining how digital transformation changes routines and work roles in knowledge-intensive work.*

**Keywords:** Cognitive technology, knowledge-intensive work, socio-technical change, processual approach

### 1. Introduction

Recent advances in cognitive technologies<sup>1</sup> such as machine learning (ML) and systems that employ models based on it have sparked organizations' interest in applying such models to perform tasks that are part of their core business processes (Mendling et al. 2018), tasks traditionally resting firmly in the human domain. Artificial intelligence (AI) is predicted to bring significant changes to the work central to the accounting field in particular (Agrawal et al. 2019), thus paving the way for more efficient use of data but also affecting the

profession itself (Acemoglu & Restrepo, 2019). While deploying ML models for knowledge-work tasks promises benefits for both the individual (via reduced repetitiveness) and the organization (in increased efficiency), such changes' socio-technical implications for work practices crucially influence the roles of knowledge workers. These merit attention. While the systems in the ideal case allow human experts to focus on more productive work, humans' input is still required in unclear situations. When, for example, an ML model relying on historical data has not been able to deduce the correct output with great enough certainty (Amershi et al. 2014), the socio-technical setting must support appropriate fallbacks.

As cognitive technologies begin to demonstrate agentic properties by taking on tasks involving more uncertainty in complex situations, these agentic information-system (IS) artifacts' position as an enabler for transferring rights and responsibilities from, or even to, human agents (Baird & Maruping, 2021) presents a pressing issue. To open the possibility of investigating how AI-induced socio-technical change is transforming interaction between humans and cognitive technologies that exhibit agentic properties, scholars can find value in a relational approach wherein the unit of analysis is not individual agents but interactions between those agents, whether humans or agentic IS artifacts. Responding to Raisch and Krakowski's (2021) call for adopting a relational ontology – moving the center of analysis from particular agents to interactions between them – to enrich understanding of AI use's socio-technical implications, I sought a balanced view of the social and technical elements via a socio-technical perspective. A socio-technical lens affords attending to the unique ways in which cognitive technologies' establishment in this context weaves together the social and the technical (Sarker et al. 2019).

<sup>1</sup> This class of technologies encompasses both rule- and learning-based systems (see Davenport & Ronanki, 2018). My work focuses primarily on the latter.

With the increasing importance of understanding the systemic outcomes of these emerging human–AI hybrid systems, I set out to improve understanding of the constellation of phenomena by tackling a critical question: *how does transition toward human–AI work influence work roles in knowledge-intensive operations through shifts in routines’ dynamics?*

With this question and a carefully considered approach, I conducted a case study that shed light on how, as an AI system’s implementation unfolds over its various phases, the interactions between human agents and agentic IS artifacts shift (Baird & Maruping, 2021; Raisch & Krakowski, 2021). The study revealed the dynamics that ultimately created a possibility for the organization’s knowledge workers to adapt and expand their work routines to accommodate the AI system’s use, with the concomitant potential for gradual, subtle shifts in roles.

The discussion begins with a review of literature on routines’ dynamics and work roles and on automation and augmentation in cognitive-technology applications. Then, Section 3 addresses methodology, describes the case setting, and outlines the data-analysis process. The presentation of findings that follows this is arranged in terms of the three main phases of the implementation process. Deeper discussion of the findings and their links to relevant literature leads into discussion of how both theory and management practice can move forward in light of the implications. A summary of the central findings and contributions concludes the paper.

## 2. Related literature

For background understanding of how transformation of roles in knowledge work arises through the formation of new routines as an AI system enters knowledge workers’ use, I surveyed the literature on routine dynamics and scholarly writings on automation and augmentation. My aim was to understand the influence of cognitive technologies – AI systems’ especially – in creating new patterns of action and changing existing ones through both automation and augmentation of the procedures for carrying out work tasks, alongside the larger processes transforming knowledge workers’ roles.

### 2.1. Routine dynamics

Although earlier scholarship regarded routines as stable entities (Nelson & Winter, 1982), research into routine dynamics introduced a performative angle on them, whereby one can explain both the stability that is continually re-enacted and the change as enactments evolve (D’Adderio, 2008), by articulating a recursive cycle of ostensive and performative elements (Feldman

& Pentland, 2003). The former comprise enacted patterns, with the rules and principles that guide the action patterns, while the performative aspect consists of what is actually done in specific performances. This way of approaching routines conceptualizes them not only as recognizable patterns of interdependent actions repeating but also as practices with internal dynamics. As Feldman et al. (2016) have noted, most routines in formally structured organizations do not seem like temporal action patterns or to show potential for change, but neither do they appear to be static or fixed things. As those authors pointed out, routines coalesce via a process of (re)production through ongoing efforts of people and things in a socio-technical system.

Moreover, one can view change in routines as either adaptive or generative (Parmigiani & Howard-Grenville, 2011; Pentland & Feldman, 2005), where adaptive change consists of bringing on exogenous changes by creating variations from outside the routines (Nelson & Winter, 1982; Pentland & Feldman, 2008) and generative change is endogenous local enactments carried out creatively by emphasizing internal dynamics and performances that foster variations and allow change to take root (Bucher & Langley, 2016; Pentland et al. 2012) where these informal practical actions render the systems more usable locally (Gasser, 1986). One can detect both types of change in the dynamic interactions among three aspects of routines: the aforementioned ostensive and performative ones plus a material aspect (Pentland & Feldman, 2005; Volkoff et al. 2007). The material dimension comprises components of routine enactment incorporating technological artifacts and the ways in which interactions between actors and components of routines take place in practice (Pentland et al. 2012). However, as Barley (1990) notes, technically driven change to humans’ ostensive and performative dynamics is likely to be bound up with material constraints (brought by any technology) that must be overcome via transformation of routines. To examine the material aspect more closely, I turned to research on cognitive technologies’ automation and augmentation capacities.

### 2.2. Automation and augmentation

Alongside the routines’ dynamics themselves, technological artifacts are fundamental factors in those routines’ change and execution (D’Adderio, 2011). If the system implemented can mediate both the ostensive and the performative aspect, the material aspect gains dominance over the performative one in that a technological artifact assumes control of the execution (Volkoff et al. 2007). Therefore, in the course of implementation, local routines can grow embedded in the material by mutual adaptation, such that the social

and the material become interwoven and mutually linked in ways that admit new possibilities for reaching work goals (Leonardi 2011). Scholars have extended their gaze beyond how technological artifacts affect the dynamic interaction of these three aspects of routines. As Raisch and Krakowski (2021) assert, the degree of automation and augmentation too affects the human/AI interaction, in combination with the humans' involvement in the work tasks. When drawing on the perspective proposed by Raisch and Krakowski, I regard automation and augmentation as interdependent in AI use: rather than sitting on opposite ends of an axis, the two cannot be neatly separated from each other.

At this juncture, some definitions are necessary. In automation, AI takes over a work task previously handled by a human, and an augmentation-based approach is aimed at employing human-AI collaboration to carry out a task (Davenport & Kirby, 2016) that demands continued human involvement (Amershi et al., 2014). The effects on humans' involvement and interactions in the socio-technical system depend on the extent to which a given implementation of a cognitive technology such as ML-based modeling brings about each of the two. For precision in referring to these technologies, my study conceptualized an ML model as composed of ML algorithms, with that model, in turn, giving the overall AI system the ability to learn from data without being explicitly programmed to do so (Mitchell 1997). An AI system, then, is made up of ML models with a user interface through which humans interact with the system. Moreover, as interactions change, humans' capability for reflection changes, with reflection often proving inherent to our interaction (Dittrich, Guérard, & Seidl, 2016). Yanow and Tsoukas (2009) define "reflection-in-action" as embedded, integrated into practice, and embodied (i.e., occurring in the midst of action without interruption to the activity in progress), in contrast against "reflection-on-action," which takes place before or after action. Reflection-in-action is especially significant when time is short and action needs to unfold quickly (Alvesson, Hardy, & Harley, 2008), while considering what might later occur or what has already occurred does not require such immediacy.

### 3. Methodology

The aim of the research was to improve understanding of how the roles and the required skills in accounting work undergo transformation with the organization's implementation of an AI system for the work. As this study adopts a relational ontology, the perspective of routine dynamics aligns well with this foundational ontological framework, as its theoretical underpinnings are rooted in practice theory, where

relationality holds a central role. For routine dynamics, the relational approach means that the aspects of routines are mutually constituted and that routines come into being as people and artifacts enact them. In other words, although the concepts can be analytically separated, the relational ontology that underpins this study and the routine dynamics perspective, the aspects of routines are treated as inseparable, and the focus is on the interactions between people and artifacts.

I found an interpretive approach appropriate for a study that builds on accountants' subjective perceptions and experiences to inform solid understanding of the socio-technical change in progress. For deeper digging into this complex phenomenon, I adopted a process-research approach (Langley 1999) to examine it within its organizational context longitudinally. Interpretive process research is especially appropriate for such efforts because the longitudinal data facilitate forming an understanding through the participants' experiences and perceptions (Langley, 1999) of how the interactions in the socio-technical systems evolved and led to transformation of skills and roles (of accountants in this case).

Conducting such a project necessitated longitudinal access, from pre- to post-implementation stages, to an organization that planned to deploy ML models in its knowledge-work processes. Once I had identified a firm in the financial-accounting field that had plans to develop and deploy an AI system that its knowledge workers would then gradually start using, I was able to reach agreement with the organization on a three-year study. This access enabled forming thick descriptions of the socio-technical change by longitudinally interviewing the accountants, along with other experts and managers who possessed essential information. The case organization was a large Finnish company that specializes in delivering financial-accounting and payroll-administration services to its clients. The company, referred to here as "A-Counting," has several local offices, throughout Finland, and its accounts payable accounting work is concentrated in a single location, the shared service center (SSC) it established in 2019 for this purpose. Its SSC is set up such that dedicated teams carry out specific financial-accounting processes for accounts payable (AP), accounts receivable (AR), and general-ledger (GL) accounting. Furthermore, the same year saw A-Counting create an AI innovation unit, which develops and implements ML algorithms to automate and augment financial-accounting work tasks. This unit strives to utilize the company's historically accumulated data in training of the AI system's ML models.

### 3.1. The case-study setting

My focus is on the accounting process influenced by the AI system designed, developed, and deployed for the purpose of generating invoice-posting predictions more efficiently. The A-Counting AI development unit's goal with the system was to free the human experts' time for more productive tasks. Before the AI system's implementation, accountants carried out the tasks connected with making correct account postings on the basis of purchase invoices' information, and they checked and validated the correctness of each account posting and VAT value on the purchase invoice. For these work tasks, the accountants had been responsible primarily for processing hefty volumes of invoices by entering account postings manually in the accounting-information system – automatic postings were set up (manually) for only invoices that reuse exactly the same bookkeeping account and VAT values.

Since the AP process involves large volumes of invoices, with the postings for each invoice consuming considerable time, AI-generated account postings constituted a high-priority use case for initial attention per the AI development unit's criteria. The accountants were not involved in choosing the work tasks for which the AI system would be used; rather, the AI development unit consulted them to learn how some tasks are carried out, in aims of obtaining a sense of how the ML algorithms and models should be tweaked so as to produce the outputs required.

The development goal was that the AI system's ML models predict values for account postings and VAT values to populate purchase invoices, thereby decreasing human experts' involvement in the invoice-handling task, which is the most laborious part of the AP process. In the design envisioned, those AI-generated predictions that are below a set confidence threshold get highlighted and listed (in a widget in the accounting-information system) for the accountant to check and either correct or validate. Via the accounting-information system, an accountant can activate the AI system client-specifically in light of the AI's assessment of its expected accuracy in that client's case. For finer granularity, the user can toggle the AI system's use at the level of specific suppliers to each client company.

### 3.2. Data collection

Data collection began in January 2020, with the first round of interviews of A-Counting accounting personnel. I followed that with three further interview rounds, to collect qualitative longitudinal data largely by means of working with the same informants who participated in earlier rounds. The interviewees varied in education and experience, ranging from recent

graduates with vocational qualifications in accounting to seasoned certified accountants, all either directly participating in the piloting and, later, use of the AI system or otherwise affected by the system. In all, 66 semi-structured one-on-one interviews were conducted at the case company, over two years (between January 2020 and December 2021). Accounting specialists and accountants involved in either piloting or use of the AI system represented 39 of these; 22 interviews were with senior accountants experiencing effects of the system; two were with team leaders, for AP and AR accounting; and there was one interview each with the accounting-process owner, the director of the SSC, and the data scientist with a central role in the AI system project. Table 1 sums the number of interviews conducted per each quarter of years 2020 and 2021:

**Table 1. Number of interviews**

	17	0	8	10	1	17	0	12
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
2020					2021			

The first-round interviews, held at the SSC, focused on gaining an understanding of the accountants' work content and responsibilities, coupled with knowledge of their initial perceptions of AI and automation tools in general. At this stage, only a couple of A-Counting accountants had been engaged in the AI system's pilot phase, and most had not been exposed to the system development in any way and had very limited understanding of AI and ML. Interviewing the accounting-process owner at that point enabled me to gain a comprehensive overview of the various accounting-related processes and the associated information systems employed to assign and coordinate work tasks at the company.

The second set of interviews took place in September to December 2020, about a month after the AI system's deployment for limited production-environment use. I used virtual meetings because the SARS-CoV-2 situation in Finland precluded interviewing the accountants on the case organization's premises this time. My camera remained on throughout the calls, for livelier interaction and to let me convey non-verbal cues (nodding etc.) signaling that, for example, I was listening while taking notes. I did not, however, request the interviewees to turn on their own cameras, and only a few did so, of their own volition. The second-round interviews with accountants covered their perceptions and experiences of AI and automation tools similarly to the first-round ones; however, by this point the AI system had entered use for about 100 client companies whose outsourced AP processes were handled at the SSC, so this round's protocol included

more specific questions related to how the system – which certain accountants on the AP team had already begun using – might have affected the interviewee’s work. A month later, in January 2021, I interviewed the SSC director, thereby gaining an understanding of the motivation for developing/using AI and its connections with A-Counting’s broader strategic aims.

I conducted the third interview round in May–June 2021, when the AI system had been in full production use for two months. The interviews covered topics very similar to the previous round’s, and the setting again was virtual. Almost all of the interviewees on the AP and AR teams had gained more experience of using the AI system since round 2, and their perceptions had evolved either through their direct experiences with it or from second-hand accounts; similarity in structure helped illuminate such developments. At the same time, though senior accountants had neither been using the AI system in the GL process nor been involved in the piloting or development efforts, they had expressed some concerns about it in the previous round, so I asked them more specific questions about how it influenced their work and whether their collaboration with AP and AR accountants had changed in any way.

The fourth interview round, conducted as virtual meetings in November and December 2021, followed a protocol paralleling that from the third round except that I was prepared to ask specific follow-up questions especially related to skills. Because I had noticed that informants in the second and third rounds had been able to offer some observations as to what new skills they might need as AI use permeates the processes more fully, I was able to enter much deeper discussion with some of the informants about how the use of AI may have started producing latent effects on their skills and ask how such change might influence their competence in the work tasks for which they were responsible.

All interviews were audio-recorded, with the exception of the one with the process-owner since such content as detailed descriptions of the accounting processes’ steps remains a trade secret. During that interview, I took general notes about what was discussed, and the occasion assisted in giving me thorough understanding of the accounting-related processes. In addition, I received internal documents that describe the AI innovation unit’s mission and introduce the team that designed and developed the AI system.

### **3.3. Analysis of the data**

The main goal behind the data analysis was to identify what had transpired in the socio-technical system as the development, implementation, and use stages unfolded, alongside how said system and the

routines involved had transformed over time. Moreover, I set out to explore what new routines had formed to accommodate the use of AI and how that shift in arrangements had affected the work roles.

In combination, the interviews I conducted, my field notes, and the materials received from the company provided a solid basis for analysis, whereby immersion in the data afforded familiarity even with subtle nuances. Preliminary analysis began with the interviews (the transcripts of which allowed me to return to the informants’ responses throughout the analysis process). Starting with the data from the pre-implementation situation, this analysis identified the main routines, their ostensive and performative aspects, and the distinct human and technological actors participating in the socio-technical system that carries out the accounting practice composed of various routines. Then, I engaged in similar analysis to examine what had changed by the time of the post-implementation interviews, when the AI system had entered wider use, and how the accountants had come to interact with it. The routines were thus revealed from the data by first identifying what were the formal and explicit procedures outlined by the company’s accounting process team and then assessing to what extent the accountants were enacting the formal procedures. Thus, analyzing the accountants’ descriptions further revealed how they were performing the work in practice and whether these tacit and implicit ways followed specific patterns. This part of the analysis also considered how the algorithms were designed, the development methods, and what work tasks were automated and augmented. Subsequently, this allowed delve deeper to how did the accountants cope with change at each stage in the development, implementation, and use of the AI system.

Once I had outlined the pre-implementation and post-implementation situation both, I began analyzing the nature of the changes in routines over time, especially in light of the background theory – for instance, was the change exogenous or endogenous and did the work exemplify validation-in-action or validation-on-action? The concepts that I draw on in this study thus provided me a sensitizing lens in analyzing the informants’ accounts. The outputs from this analysis helped me pinpoint the changes in interaction dynamics among the accountants, accounting-information system, and AI system, along with the ensuing alterations in the routines involved. Therefore, identifying how the transaction data was flowing through the formal accounting procedure all the way to it being added as information to records and reports was essential. Starting from the transaction data being received to the accounting-information system, what were the roles and related responsibilities in processing it further, and what interactions occurred during the whole process to arrive

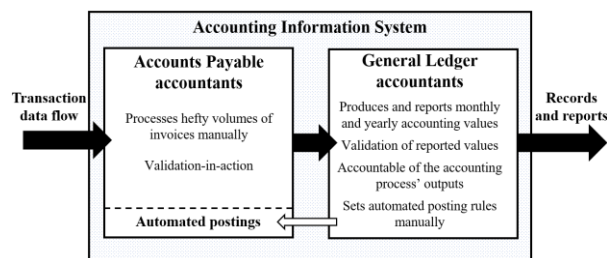
at validated and correct accounting information. In the end, I was able to capture the pre- and post-implementation composition of the socio-technical system by means of diagrams of both stages, thus illustrating how that system evolved over time.

## 4. Findings

The study identified central events and processes that came to shape the accountants' roles through changes in routines. With the subsections below, I discuss three constellations of these, those appearing in each of the three main phases of the AI system's development and proliferation. Ultimately, they coalesced in human–AI routines in the case company. This gradual move toward the routines represents transformation in the work tasks' division, not merely the tasks themselves, and in the works roles. Here, humans come to enact the work process in a new way.

### 4.1. The pre-implementation phase

A-Counting's AI system design and development project began in June 2019 with the appointment of the AI innovation team, consisting of two data scientists and two service designers. The team's first aim was to develop an AI system that would assist accountants in the AP process, whose work duties encompass populating invoices with account and VAT data that comply with accounting regulations. Figure 1, below, illustrates the socio-technical system as it existed before implementation of the AI system: two deeply embedded groups of accountants with specific dedicated routines and responsibilities, who rely primarily on the accounting-information system to carry out their work.



**Figure 1. The accounting process and work roles before the AI system's implementation.**

Beyond the aforementioned trivial rule-based automated postings that a GL accountant is responsible for setting up manually (for specific suppliers' invoices that always involve the same recurring costs), no automation or augmentation technologies were visible. The dashed line in Figure 1 signals that although automated postings were part of the AP process, the AP

accountants did not interact with the automation. While both AP and AR accountants regarded the manually established automated postings as helpful, these postings, which the accountants can always rely on to be correct, represented only a small proportion of all invoice postings. The AP accountants had to process the vast majority of invoices manually and validate the account number and VAT value postings "in action" by glancing at specific contextual information in the invoice to verify their correctness. This reflection taking place in the moment, as validation-in-action, plays an important role in enacting the routine of making sure all invoices' postings are correct.

To move the proposed AI system forward, the AI innovation team developed a pilot version. Selected AP accountants were asked to test it and give feedback: in the pre-implementation phase, a small group of accounts-payable accountants participated in the AI system's piloting, which entailed reporting on its functions and indicating how it should be developed so as to accommodate the accountants' needs in a manner that honors accounting standards.

At this stage, the data scientists' work centered on making sense of the AP experts' accounting routines and, accordingly, crafting ML algorithms that function in accordance with the accounting standards by emulating the accounts-payable accountants' invoice-checking and validation process as faithfully as possible. However, the data scientists, while proficient in creating ML algorithms and models, struggled to grasp the very basics of accounting routines – for example, which account and VAT values are to be used for postings for the various purchase invoices. In the pre-implementation phase, they had to grapple with such facets of the AP process as why certain parts of handling the invoices and setting the associated postings are handled in one way sometimes and in another manner in other circumstances. Piloting and receiving feedback on the algorithm development hence had a crucial role in developing the ML models: the data scientists needed for apprehending what sort of information is checked before submission. Still, because they received feedback verbally and limited their user observations to only a couple of brief instances, the system's developers came to terms mainly with the ostensive aspect of AP routines. Therefore, the algorithms of the AI system mirror this understanding, emulating almost exclusively the ostensive dimension – and even that to quite a limited extent.

### 4.2. The system-implementation phase

With the piloting complete, the AI innovation team began preparing to bring it into limited production use for selected customers. Hence, September 2020 ushered

in the AI system's implementation phase with bounded deployment that made it a system within a larger socio-technical system.

As the accounts-payable accountants whose client companies were within the limited deployment's scope begin to use and interact with the AI system, both major and minor issues with its performance began arising. Notwithstanding the pre-implementation piloting, erroneous AI-generated postings were commonplace as the second phase proceeded, with the system even flagging some postings as guaranteed to be correct although they contained errors. This exogenous change required the accountants to approach the AI system's output with caution and adapt their routines accordingly. The change in routines consumed considerable amounts of their time, since they had to check every posting that had the slightest chance of containing errors. It had become clear that the ML models could not emulate the routine of validating the correctness of invoices' postings.

Albeit tedious and time-consuming, scrutinizing numerous erroneous postings improved the accounting experts' understanding of why specific postings are handled in a certain way. Since they now had to reflect on the information on each invoice, validation-in-action became an essential activity. This unintended development stemming from the AI system's breakdown helped accountants express what they were doing, and it helped the data scientists respond to the need to find both bugs and deeper issues in the relevant ML model, through a combination of discussion with the accounts-payable accountants and revision to the algorithms created for the model.

Although some issues were not resolved swiftly, by March 2021 the data scientists had rectified all the critical issues with the AI system and improved the ML model's output accuracy significantly. At this point, the AI system was able to emulate both the ostensive and the performative aspect of the process reasonably well for the client companies within scope thus far. That is, the artifact (the material aspect) could take over responsibility for the performative element for the most part. Although the data scientists had been able to make incremental improvements to the AI system as the implementation phase continued, the final breakthrough in improving the ML model's accuracy came in February 2021, when the lead data scientist had finally isolated and resolved the last remaining critical issue that had caused errors in VAT posting predictions. With this fix, the accountants could finally start using the AI system in the intended manner, for checking only the uncertain posting predictions and validating all accounts-payable postings by means of a validation report in the accounting-information system. After a phase of flux that entailed adaptive change, the AP

accountants who were using the AI system commenced local enactments with its use and began enacting their routines in a new way to accommodate the novel interactions and endogenous, generative change in the human-AI hybrid routine. Moreover, as use of the system spread among the accounts-payable accountants, the managers adjusted the organization's work-process guidelines. When the next stage began, the accountants were expected to follow the formal steps specified.

### 4.3. The AI system's post-implementation phase

With the AI system in full production use in March 2021, the AI innovation team shifted from active participation in its development to maintenance mode, in the post-implementation phase. The interaction established in October 2019 between the AI team and the accountants came to an end when the system was deemed to have answered the first business case for AI via production use, and feedback and communication routines wound down. While the innovation team was interacting with the accounting process only loosely through the AI system now, that system had become deeply embedded in the formal accounting process and individual accountants' routines. Figure 2 depicts the results: with full implementation of the AI solution, the socio-technical system was established as a system within a system, the accountants handling the AP routines were situated in close interaction with it for every client company in question, and accountants were adjusting their practice.

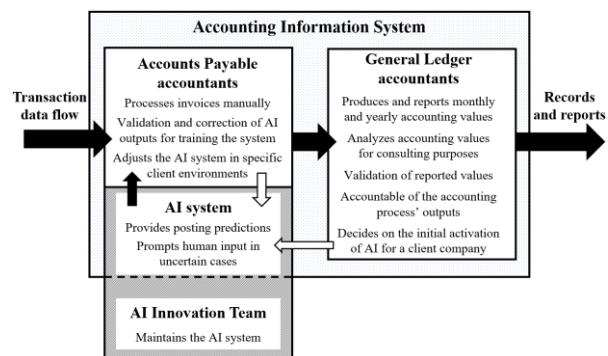


Figure 2. The accounting process and work roles, transformed after the implementation.

The accountants conducting the AP routines noted particular changes wrought via the socio-technical shift. They found that the AI system was expediting their work, irrespective of erroneous postings coming up every now and then. Because the AI system is working as intended and the material aspect now dominates the performative aspect in the dynamics of routines, the

newly formed human–AI hybrid routine generates efficiency gains – it saves time by automating the repetitive task of processing invoice data and, thereby, permitting higher throughput for the accounts-payable process. Furthermore, the general-ledger accountants have a more real-time view of the client companies’ financial situation since many of the invoices get processed as soon as they enter the accounting-information system. Since AP accountants no longer experience a need to check posting predictions that are above the confidence level specified, they can focus instead on fully validating and correcting those posting predictions that are below that level, which a widget in the accounting-information system presents in list form.

Even though the turnaround time has decreased and the AP accountants can finish more client work in a given amount of time than was possible before, they see themselves as doing the same work. Yet they wonder whether they might be taking the AI system’s posting recommendations for granted without noticing that they are doing so, a phenomenon that is especially likely when an AI system has shown consistent reliability over time. This perception expressed in the interviews points to one possible downside of activities’ augmentation – potential lack of necessary validation-in-action. Moreover, this human–AI hybrid routine alters the nature of some validation work: high-confidence automatically created postings do not get validated until presented in the validation report at the end of the formal accounts-payable process. This invokes a shift to validation-on-action in that the AP accountants validate the actions of algorithms by looking at abstracted values in a report devoid of contextual information, going back to consult the invoices only if something stands out as deviating from the regular pattern of historical postings evident from the report.

Another consequence of the implementation is that the accounts-payable accountants now carry out the routine of supervising the AI system’s performance. They monitor its performance and can deactivate the AI system for a specific client company if it performs poorly in that client’s context. Furthermore, the humans’ role includes augmenting the ML models. By correcting the postings that lie below the confidence threshold, the accountants refine the body of data from which the ML models learn.

The AI system has become embedded in the accounting-information system, overall, and the newer AP recruits especially do not even recognize it as a separate system (in marked contrast to the piloting accountants who had wrestled with it earlier). What they interact with is one widget among many in the user interface of the accounting-information system.

## 5. Discussion

Although the two configurations of routines are not discontinuous – and still exist side by side to some extent – the implementation of the AI system precipitated changes in interactions and routines while also sparking discussion of the roles and responsibilities of the accountants woven into both socio-technical system configurations, with their accompanying specific routines.

### 5.1. Implications for theory

The findings that are illustrated in figures 1 and 2 provide a clear picture of how human–AI hybrid routines may emerge when an AI system both automates work tasks and augments human experts’ procedures with recommendations that begin to transform the knowledge worker’s role. In the case company, the implementation examined set transformation of work practices and roles in motion as the organization began a transition toward human–AI work. Importantly, the readjustment of work roles is a more arduous and complex process than just beginning to use an AI system in a manner suggested by earlier configurations of routines (e.g., Grønsund & Aanestad, 2020). At A-Counting, the AI-based system started performing some of the routines that accountants previously carried out themselves, especially ones that call for reflection-in-action (Yanow & Tsoukas, 2009) during algorithmic output validation. They thus chip away at the main source of informal skill maintenance over time. Therefore, the intended augmentation for the knowledge worker gets twisted into substitutive automation in consequence of the humans’ local enactments in routines without an appropriate formal procedure that imposes safeguards from the organization’s side. The case study illustrates humans growing attuned to the organization’s institutional logic of efficient performance, thus tapping in to the material aspect of routines that provides for doing the work more quickly without heed for the degenerative dynamics that begin to unfold. Obviously, the promise of dynamically forming task assemblages (Rai et al. 2019) by means of transition to human–AI work will go unmet if the organization does not introduce and enforce formal practices that support suitable enactment of routines’ material side. The absence of proper practices and solid enforcement of them can feed work-role drift also, since the responsibilities are not clearly defined from a technical standpoint.

The case of A-Counting supports the picture provided by the theory with regard to the data scientists’ limited perspective also. Because the workers developing the AI system comprehended only the

ostensive aspect of accounts-payable routines at first, a situation arose in which the material aspect reflected neither the ostensive nor the performative aspect of those routines. The problems that ensued during the development process (of multiple types and on several scales) attest to the need for balance as articulated in the literature. The data scientists had to become able to grasp the performative aspect too – i.e., how the invoices are processed in practice, which diverged from the formal work process that they were building through the ML models. The study highlights that forming a properly functioning material aspect to the conjuncture requires dynamic, well-balanced interaction between the ostensive and performative dimensions. If either is lacking, the material aspect of routines cannot adequately capture the routines that the AI system is an attempt to emulate.

The study also sheds light on the skill needs (old and new) involved in the processes and their transition. As the socio-technical system adjusted, it manifested a shift from the need to apply skills in action to the need to interpret outputs. The AP experts' work became more akin to GL accountants' procedures, which necessitate dealing with abstract numerical values, making sense of them, and validating information in reports. As transformation unfolds, there looms a risk of losing the experts' nuanced understanding of financial information in that the principal window to validation now is reports that contain just the final values instead of a holistic reflection process wherein the accountant is forced, through practice, to assess actively whether the posting is correct. Therefore, the shift from validation-in-action to validation-on-action as such AI systems take root calls for formation of new metaskills that support active reflection as a core activity.

Finally, the findings cast doubt on the notion that employing AI systems (or cognitive technologies more generally) inevitably unlocks human capacity to perform non-routine tasks (Nedelkoska & Quintini, 2018). If the work role is narrowly specified, as it is for AP accountants, the human experts are likely to perform the same tasks, just accomplishing more in the same time. Drawing on Sarker et al.'s (2019) concepts of instrumental and humanistic outcomes, one may conclude that narrow work roles involving repetitive tasks are unlikely to yield better humanistic outcomes; on the contrary, intensification of work might well follow. Tellingly, it appears that hopes of automation and augmentation relieving humans of the burden of monotonous work were not fulfilled in this case.

## 5.2. Management implications

The findings from this study point to the centrality of managers' role in establishing formal practices,

through exogenous change, that prove capable of forcing specific local enactments of routines to coalesce. Because local adaptations of accountants' (and others') routines can act to the detriment of proper human–AI hybrid routines taking hold, organizations must actively pursue sustainability of socio-technical resources amid the transition to human–AI work. If the organization does not enforce formation of proper routines, reaping such work-task assemblages' full benefits is impossible, and any efforts to cultivate their capabilities remain half-measures.

Accordingly, managers are recommended to create routines that are able to steer the organization toward proper practice as the cognitive technology is nurtured and takes hold. This should, in turn, aid in moving from the AI system's application as mere substitutive automation to a healthy approach of augmentation that opens the possibility of rich, appropriate transition to human–AI work.

## 5.3. Limitations and opportunities for future research

The study's collection of data with semi-structured interviews and the scope of data analysis afforded rich analysis but represent limitations also. Fleshing out the perspective with an ethnographic study could provide more nuanced data and support multifaceted understanding, especially of performative factors in routines, by supplementing the data collected via interviews. In addition, future efforts should expand the preliminary data analysis that I conducted, to provide an in-depth account of the interactions, routines, and roles as well as how these evolve over time. While the AI system implementation examined in the case study was successful in that it utilized the user interface of the accounting-information system to support an integrated experience and the domain experts could continue drawing on their domain knowledge without having to learn statistics skills, more time and other research settings could reveal further downsides bundled with such success. For instance, the AI system's algorithms might end up "black-boxed," with the domain experts having no skills that prepare them for understanding how the algorithms work or interpreting how the algorithms arrived at the AI-generated predictions. Future research could look into such phenomena.

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